

Factors Affecting Probability Matching Behavior

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ABSTRACT

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In life, people commonly face repeated decisions under risk or uncertainty. While normative economic models assume that people tend to make choices that maximize their expected utility, suboptimal behavior – in particular, probability matching – is frequently observed in research on repeated decisions. Probability matching is the tendency to match prediction probabilities of each outcome with the observed outcome probabilities in a random binary prediction task. For example, when people are faced with making with a sequence of predictions, such as repeatedly predicting the outcome of rolling a die with four sides colored green and two sides colored red, most people allocate about two-thirds of their predictions to green, and one-third to red. The optimal strategy, referred to as maximizing, would be to choose the outcome with the higher probability in every trial in the prediction task.

Various causes for probability matching have been proposed during the past several decades. Here it is proposed that implicit adoption of a perfect prediction goal by decision makers might tend to elicit probability matching behavior. Thus, one factor that might affect the prevalence of probability matching behavior (investigated in Studies 1 and 2) is the type of performance goal. The manipulation in Study 1 contrasted single-trial prediction with prediction of four-trial sequences, which it is hypothesized might create an implicit perfect prediction goal for the sequence. In Study 2, three levels of goal were explicitly manipulated for each sequence: a perfect prediction goal, an 80% correct goal, and a 60% correct goal. In both studies it was

predicted that more matching behavior would be observed for those who have a goal of perfect prediction than those who have a more reasonable (lower) goal. The results of both studies, conducted in an online worker marketplace, supported the goal-level hypothesis.

The second factor proposed to affect the prevalence of probability matching is the type of conceptual schema describing the events to be predicted: independent events or complementary events. Study 3 investigated the effects of schema type and abstraction level of context on matching or maximizing behavior. Three abstraction levels of stories were included: abstract, concrete random devices, and real-world stories. The main hypothesis was that when the two options to be predicted are independent events, less matching and more maximizing behavior should be observed. Data from Study 3 supported the hypothesis that independent events tend to elicit more maximizing behavior. No effects of abstraction level were observed.

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Chapter I Introduction

Probability matching is the tendency to match prediction probabilities of each outcome with the observed outcome probabilities in a random binary prediction task (Fiorina, 1971; Fantino & Esfandiari, 2002; Shanks, Tunney, & McCarthy, 2002). This is non-optimal or “irrational” behavior. For example, when people are faced with a sequence of prediction tasks (repeated trials), such as predicting the outcome of rolling a die with four sides colored green and two sides colored red, most people allocate about two-thirds of their predictions on green, and one-third on red. This *probability-matching* prediction strategy is sub-optimal; the optimal strategy is maximizing, meaning to choose the outcome with the higher probability in every trial in the prediction task.

In real-life, people do face repeated decisions under risk or uncertainty. For example, in the stock market, people are making repeated decisions to buy or sell a certain stock whose price may increase or decrease; companies make repeated decisions about hiring students who graduated with certain degrees or from certain colleges, believing that these qualifications affect the probability of success of the new employee. It is of social importance to help people to make optimal decisions under these circumstances in real life so as to maximize their expected utility.

The use of probability-matching strategies has been a long-standing puzzle in decision making research, because use of the maximizing strategy offers a higher expected payoff. Researchers are particularly interested in this topic because the probability-matching phenomenon is not consistent with normative economic models incorporating the assumption that people tend to make choices that maximize their expected utility (James & Koehler, 2011; Vulkan, 2000).

This probability-matching phenomenon had been found back in the 1950s and 1960s (Humphreys, 1939; Edwards, 1956; Herrnstein, 1961), and has been a well-established pattern in humans since the seminal work by Grant, Hake, and Hornseth in 1951. Many studies have been done investigating possible explanations of why people adopt this strategy in experimental tasks. Basically, there were several perspectives taken by these studies.

One general research perspective is to have healthy adults participate in experiments of prediction tasks under different conditions (different experiment designs and task apparatus, probabilities of outcomes, payoff policies, feedback, etc.). These studies have proposed various accounts of probability-matching behavior. There are static rules which neglect any effect that learning processes might have, and just focus on the probabilities of outcomes, such as Edward's *Relative Expected Loss Minimization Rule* (1961, 1962), and Simon's *Minimal Regret Rule* (1976). Another perspective was taken by Arrow (1958) and Gittins (1989), who focused more on the dynamic learning process. Stochastic learning theory is also one of the explanations, which restrict attention to the memories of one previous trial, and assumes that the choices are affected by reinforcement from last trial (Bush and Mosteller, 1955). Some researchers believe that probability matching is the result of “overthinking”, that people are looking for patterns in the random sequences (Restle, 1961; Yellott, 1969; Catania & Cutts, 1963). However, others believe probability-matching to be a by-product of “under-thinking”. For example, Braveman and Fischer (1968) found that by giving participants more instructions on the study and more hints on the strategies, they choose the maximizing strategy more often.

Vulkan (2000) reviewed many studies on probability matching, and concluded that these studies suggested that the monetary payoff and number of trials have a positive influence on their

learning towards maximization; and that behavior partially depends on the last trial's actual outcome (if feedback is given to participants).

Major criticisms of these studies have involved the randomness of the sequences. Back in the 50's and 60's, many studies were carried out in paper and pencil format, and the “random sequences” were pre-written on a piece of paper, with certain outcome, for example, seven option A and three option B. Since the outcome of each trial is pre-determined, as well as the total number of each binary outcome, the trials are not identically and independently distributed (Vulkan, 2000). This fact may also raise skepticism in the participants about randomness of the sequence, because it is hard for people to believe that a pre-written sequence is random (Hertwig & Ortmann, 2001). Another criticism is that these studies only looked at the data at a group level, but it is very likely that different subgroups or different local strategies affect the probability matching phenomenon (Shanks, Tunney, & McCarthy, 2002). In Vulkan's review (2000), it is also pointed out that when the difference in the total monetary payoffs between the probability matching strategy and the maximizing strategy is not large enough, there may not be enough motivation for learning the optimal strategy.

The other general research perspective is to study different groups of subjects other than just healthy adults, and compare their results. For example, studies have been carried out on animals, children, and brain-damaged patients, as well as studies that compare people with different level of mathematical abilities. Some studies have found that animals do better than human beings in simple prediction tasks, more often choosing a maximizing strategy over a probability-matching strategy (Parducci & Polt, 1958, and Wilson & Rollin 1959; Herrnstein, 1961; Edwards, 1956, Brackbill & Bravos, 1962). Specifically, pigeons and rats can pick up a maximizing strategy quickly, while chimpanzees start with a probability-matching strategy and

soon switch to maximizing (Douglas & Pribram, 1966), and human beings persist in probability-matching strategy for a longer time. In human beings, from children to adults, along with human cognitive development, the performance in this task gets worse as age increases (Derks & Paclisanu, 1967).

In recent years, enthusiasm to study probability matching has reignited, especially in economics, where the basic assumption is that people choose normatively to maximize their utilities. Probability matching is a prevalent phenomenon that challenges such “rational” assumptions. Researchers also carried out various experiments to uncover the cause of probability-matching behavior in random binary prediction tasks (also referred to as simple prediction tasks, Unturbe & Corominas, 2007).

Recent studies also commonly used simple prediction tasks, both on human beings of different age and on animals. However, compared to previous research, recent studies have adopted some new approaches or perspectives. First of all, computer programs are commonly used to generate independent and seemingly dynamic random sequences (they are actually pseudo-random due to the generating mechanism). Second, while previous studies had focused on behavior (Edwards, 1961; Tversky & Edwards, 1966), recent studies have paid more attention to self-reported strategies (Gal & Barron, 1996; Stanovich & West, 2008; West and Stanovich, 2003). Moreover, there have been recent neurological studies carried out on brain-impaired patients (Gazzaniga, 1989; Goldberg, 2001; Wolford, Miller, & Gazzaniga, 2000).

Recent studies cannot find agreement on what strategy or mechanism is leading to probability matching (Otto, Taylor & Markman, 2011). Several explanations of probability matching phenomenon have been proposed in the area of decision making. One account of probability matching is the dual-systems account (Evans, 1984, 1989), which proposes that

probability matching is a fast, effortless process by the intuitive system (Koehler & James, 2009, 2010; West & Stanovich, 2003), while the maximizing strategy is the product of rational thinking, thus of the rule-based system. Another account is “expectation matching” (Otto, Taylor & Markman, 2011), which aligns closely with the dual-system account. Expectation matching is believed to result from processing by the implicit system of the brain. When people are using this system, for example due to high working memory load, they should allocate their choices according to the estimation of observed outcome probabilities. Reinforcement learning is another possible account for probability matching proposed by researchers, e.g., the “Win-Stay-Lose-Shift” strategy (Herrnstein, Rachlin, & Laibson, 2000), which assumes people stay on the same alternative until they get a negative feedback event. This account assumes that people depend on short-term memory of observed outcomes, which serve as reinforcers. Furthermore, many researchers have invoked pattern-searching accounts (e.g., Gaissmaier & Schooler, 2008; Unturbe & Corominas, 2007; Wolford, Newman, Miller & Wig, 2004). It is argued that participants have a hard time resisting finding patterns, no matter whether there is one or not, and regardless of what they are told about the randomness of the sequences.

Some researchers studying brain-impaired patients have suggested that different brain hemispheres are responsible for probability matching and maximizing respectively (Wolford, Miller, Gazzaniga, 2000; Gazzaniga, 1989; Goldberg, 2001). Bechara and Damasio (2005) argued that probability matching is enabled by human being's better developed neural mechanisms, therefore probability matching behavior occurs because human have the ability to respond to the outcome with lower probability while animals or children do not.

From the studies about animals and children described above, it seems that probability matching is a by-product of over-thinking by cognitively more developed human beings, and this

misguided pattern search is why human beings do worse in the prediction tasks than animals. However, dual-systems researchers have found that with more training (Shanks, Tunney, & McCarthy, 2002), people change from a probability-matching strategy to a maximizing strategy, indicating that probability matching is actually a by-product of under-thinking. James and Koehler (2011) suggested that use of probability matching is possibly described by a U-shaped function based on cognitive ability, whereby maximizing occurs both with too little thinking (due to association learning) and with too much thinking.

We believe there are several factors influencing people's choice of strategy in the simple prediction tasks. Mainly, people show probability matching due to adopting unrealistically high goals for predictions. In order to achieve the goal of perfect prediction in predicting a sequence of binary events, participants believe that using the probability-matching strategy is the only possible way (if they are lucky enough), while using the maximizing strategy seems to mean losing a small portion of the sequences for sure (because obtaining a sequence consisting of all the same outcomes seems “impossible” to them). In this case, the choice of strategy may be viewed by the decision maker as a problem of choosing between a risky success and a sure failure. If this hypothesis is true, we should not be surprised to see robust probability-matching behavior. In this paper, I will also test several other hypothesized factors that may have influence over the prevalence of probability matching in such tasks.

Research Questions

In this study, we propose that several factors may affect people's probability matching behavior, including the specific performance goal adopted by the decision maker, the level of

probability bias of the random events, and the type of schema for the random event and the problem context.

First, we are interested in testing whether *the nature of the prediction goal* plays a role in strategy people choose. Specifically, we suspect that trying to predict a binary random sequence perfectly will lead to probability matching, whereas a goal that is more realistic (e.g., relatively good prediction like 70% correct) may yield more use of a maximization strategy. The idea is that when trying to do perfectly in a simple prediction task (SPT), people think it crucial to generate a sequence that is *representative* of a random binary sequence. In this paper, we will study this factor in two separate studies. In one of the studies, the perfect-prediction goal will be emphasized in one of the conditions. In this condition, participants will be asked to predict four events in a row, and will get a bonus payoff only if they can predict all four trials perfectly; whereas in the other condition, they can earn a bonus pay for every single trial that they predict correctly. This manipulation may be effective because in a recent study (Chen & Corter, 2006) investigating people's risk preference in repeated trials of description based tasks, it was found that people do even worse (i.e., fewer expected value-maximizing decisions are made) in prospective multiple-trial choice than in single-trial choice. In another study, we will manipulate the level of goals for prediction, by offering bonus pay for certain levels of performance.

A second factor is the probability level of each decision option, in that we believe different probabilities of the more likely event will lead to different levels of probability matching, and would yield different learning rates towards the optimal strategy. If the best option has a high probability such as 80% or 70%, there is a clearly discernable maximization strategy which is optimal. However, if the probability for the two options are very similar, or in an extreme case, 50%-50%, people may behave differently. Pigeons tend to choose one of the sides

and stay there when the two options have the same probability (Herrnstein and Loveland, 1975), but we expect people to show more matching behavior, if the representativeness heuristic affects people's behavior in this type of task.

Moreover, the type of schema for the random event (whether the options are independent events or complementary with each other) may make a difference in terms of people's strategy choice. *Complementary events* means the two (or more) options are mutually exclusive, i.e., only one can happen each trial. So far, most probability-matching studies have used this kind of event. *Independent events* means the options are independent from each other, and the occurrence of one does not affect the other. So in this case, two options might both happen in the same trial. Studies of repeated decisions under uncertainty or risk tend to use independent events (e.g., Grosskopf, Erev, & Yechiam, 2006; Yechiam & Busemeyer 2006). In complementary events, there are many reasons for people choosing probability matching strategy (although the reasons may be irrational), however, in independent events, we expect more maximization.

The fourth factor we are interested in is the problem context of the events (abstract or concrete). This factor refers to the description of the context of a random event, meaning whether the task is described within a specific "real-world" context, or an abstract context. It has been found that people often use inference rules that are learned through experience, thus are context-dependent, called "pragmatic reasoning schemas" (Cheng & Holyoak, 1985; Cheng, Holyoak, Nisbett & Oliver, 1986). Reasoning in abstract and concrete contexts is believed to involve different cognitive abilities, in that a task free of contextual cues would be more dependent on cognitive processes involved in rule-generating and rule application (Unturbe & Corominas, 2007).

Chapter II REVIEW OF LITERATURE

Overview of Probability Matching Research

Recent research has considered the issue of when probability matching (as opposed to maximizing) behavior tends to emerge, and possible cognitive mechanisms that underlie this tendency to probability-match. In this section, a brief summary of current explanations and related studies for probability matching behavior will be given.

1. Reinforcement Learning

One line of thinking has attributed probability matching to reinforcement learning mechanisms (Vulkan, 2000). Back in the 1950s, stochastic learning theories (Bush and Mosteller, 1955) were proposed that assume that people restrict attention to memories of one trial back, and their choices are reinforced by the result of that trial. These theories also assume that the strength of reinforcement is directly related to the magnitude of payoffs. However, there are other researchers who believe that monetary payoff is not the only factor that plays an important role, and that other factors play a role, such as framing effects and “negativity effects”. It was also shown that people are able to respond to events four or five trials back in the sequence (Anderson & Whalen, 1960; Goodnow, 1955; Restle, 1961).

Another theory is that probability matching behavior is a byproduct of a local decision process called “Win-Stay-Lose-Shift” (Herrnstein, Rachlin, & Laibson, 2000; Gaissmaier & Schooler, 2008). Win-Stay-Lose-Shift means people keep choosing one of the options until they receive negative feedback, whereupon they change to the other alternative. This theory assumes

that the decision maker maintains a short-term memory for the most recent response and outcome, as with reinforcement learning in repeated choice tasks (Sutton, & Barto, 1999). It was pointed out that Win-Stay-Lose-Shift could be a smart strategy under some circumstances (Shimp, 1976), but in the prediction tasks discussed in this paper, it certainly is not, since this strategy will lead to probability matching for sure. Kareer, Lieberman & Lev (1997) also reported supportive results for this reinforcement account: they found that people with weak short-term memory were more likely to choose maximizing strategy.

2. Expectation Matching

One candidate explanation is that probability matching arises from a relatively intuitive assessment process called *expectation matching* (Kogler & Kuhberger, 2007; West & Stanovich, 2003; Koehler & James, 2009), where the decision maker's responses are the result of integration of past outcome information (Sugrue, Corrado, & Newsome, 2004). In other words, people use the heuristic of allocating their choices according to an assessment of all of the observed outcome probabilities (Koehler & James, 2009). This idea came originally from Tversky and Kahneman's (1971) research on people's perception of randomness. They found that when people are asked to generate a random sequence, they are likely to use a similarity-based rule, so that the generated sequence has each outcome proportional to its probability. This heuristic is called *representativeness*.

James and Koehler (2011) studied the relationship between probability-matching and expectation generation, and found a significant relation between them. They hypothesized that when people's attention are drawn away from the sequence as a whole, and towards individual trial's outcomes, this would reduce people's sequence-wide expectation, thus, will result in less

probability-matching behavior. In their studies, there were two conditions: one is sequence prediction only (meaning to predict the whole sequence at once without experiencing it), and the other one is trial-by-trial prediction (meaning to experience the sequence and predict the outcomes trial by trial). The results suggested that experience prediction yielded more maximizing strategy at the end of the sequences compared to sequence-prediction condition. In another study, they conducted a survey that has two different focuses: global-focus of the sequence, and local-focus of the trials. Results suggested that local-focus condition led to more maximizing strategy than global-focus condition.

Based on the explanation above, James and Koehler (2011) argued that probability matching could be a sequence-wide intuition formed from life experience. So this conclusion could explain why young children and animals do not choose probability-matching strategy as often as adults, in that they have not formed this intuition due to lack of life experience. Other researchers supporting this idea also argued that human did worse in the prediction tasks than animals because human beings brought the interfering history from life experience (Arkes & Ayton, 1999; Goodie & Fantino, 1996).

3. Dual-Systems Account

Another explanation of probability matching is the dual-systems account. Dual-systems theory assumes two processing systems: a rule-based reasoning system, and an intuition-based or associative learning system. Processing by the rule-based reasoning system will lead to rational choice, which is the maximizing strategy in our task, while activation of the intuition-based system will lead to the probability-matching strategy, due to lack of deliberation. Probability matching is believed to be a fast effortless process by the intuitive system. This view assumes

that people who show a probability-matching strategy deliberate very little prior to making the choice, or such deliberation did not produce the maximizing strategy (Kahneman & Frederick, 2002).

This account is supported by many studies from different perspectives. First, studies have shown that people with higher cognitive abilities are more likely to maximize and less likely to match (Stanovich & West, 2008; West & Stanovich, 2003). These researchers claimed that people with lower cognitive abilities lack the ability to deliberate and thus cannot come to the rational solution to the prediction tasks.

Second, with more training and more clear instructions given to participants, researchers found increasing maximizing strategy adoption in the predictions tasks. Goodie and Fantino (1999) found that after 1600 trials, people gradually learned to maximize. Braveman and Fischer (1968) reported more maximizing strategy implementation after giving people clear instructions in terms of the optimal strategy.

Third, in Koehler and James' (2009) study, people who adopted a probability matching strategy in the prediction tasks later admitted that maximizing is a better choice, when they were offered this strategy.

Fourth, when participants were asked to recommend a strategy for doing this task before they actually start, their choice of maximizing strategy increases (Fantino & Esfandiari, 2002).

Fifth, when participants were asked to imagine themselves as “statistician” while carrying out the prediction task by Kogler and Kuhberger (2007), they also adopted a maximizing strategy more often than the control group.

Lastly, the prediction task was adapted to single split-brain patients, and it was found that the two strategies were related to activity by different parts of the brain. The left hemisphere

seems to be responsible for probability matching (Gazzaniga, 1989; Goldberg, 2001) and the right hemisphere is responsible for the maximizing strategy (Wolford, Miller, & Gazzaniga, 2000).

However, some researchers have reported results challenging the dual-system account of probability-matching. First, young children and animals did better than grown human beings in the prediction tasks. The dual-system theory should predict the opposite result. Also, when working memory load is high, the choice of maximizing strategy actually increased in one study (Wolford, Newman, Miller, & Wig, 2004). This also contradicts what a simple dual-systems account would predict.

4. Pattern-Search Account

Alternatively, other studies have proposed that people might be searching for patterns of the sequences, and thus seemed to be probability matching from their predictions. Yellott (1969) investigated this idea by giving feedback exactly the same as the participants' prediction. This study found that people were manipulated, and in the questionnaire afterwards they claim that they were successful finally in finding the rules or patterns of the sequences. Catania and Cutts (1963) also reported unreasonably complicated self-report strategies.

One of the pieces of supporting evidence is that while nonhuman beings such as rats or pigeons maximize the outcome by choosing the most probable option (Bitterman, 1975), human persevere in the suboptimal strategy of probability matching (Birnbbaum & Wakcher, 2002; Fiorina, 1971; Vulkan, 2000); in fact, it seems that the more evolved the mammal, the worse its performance (Unturbe & Corominas, 2007). Wolford, Miller and Gazzaniga (2000) found that left hemisphere of the brain is responsible for interpreting previous experience, so they believed

that animals did better than human beings because people are searching for patterns in the sequences and trying to interpret the sequences in terms of patterns.

Wolford et al. (2004) found pattern searching to be hindered by high working memory load, and in this case more maximizing was observed. Koehler and James (2009) investigated the idea that probability matching may be related to an explicit search for patterns in temporal sequences, but found that it was common even when this type of information was suppressed (Gal & Baron, 1996; Kogler & Kuhberger, 2007); this result has been suggested by other researchers too (Unturbe & Corominas, 2007). Similar to this idea of pattern matching, some believe that people are doing hypothesis testing of the rules or patterns of the sequence.

Gaissmaier and Schooler (2008) pointed out that it is easier to convince people that something is structured than random (Hyman & Jenkin, 1956), thus it is possible that the misconception of randomness is the cause of pattern search. They argued that probability matching could be a smart approach, because if there is a pattern, the ones who search for patterns would find it sooner than those who do not, and will have better performance as a result. Therefore, probability matching requires high working memory capacity, while Win-Stay-Lose-Shift strategy only requires low working memory capacity. Restle (1961) also found that people have hard time believing the randomness of the sequences, thus would search for patterns even if there is none.

5. The Role of Unrealistically High Goals

Fantino & Esfandiari (2002) suggested that probability matching is the result of adopting unrealistic high prediction goals, with the implicit or explicit adoption of a perfect-prediction goal leading to matching. They cited Levine's (1974) and Weisberg's (1980) studies about human problem solving to justify this assumption. Fantino and Esfandiari (2002) believed that by

informing participants 1) the probability of each outcome and 2) the fact that in the long run they cannot achieve better than the probability of the more likely outcome, which is 75%, they would tend to choose maximizing more often. In their study, they informed one group of participants that they could be correct on no more than 75% of the trials, while no information like this was given to the other group. However, “optimal behavior did not occur whether or not subjects were given these instructions”. In the discussion, they mentioned that one possible reason for the result is that “perhaps subjects did not believe our instructions”.

Gaissmaier and Schooler (2008) suggested that people do not believe in randomness of the sequence and try to outperform the optimal maximizing strategy. Wolford, Newman, Miller and Wig (2004) found that the more people believe the randomness of the sequences, the more they tend to maximize. These arguments and results can be seen as consistent with the pattern-search account of probability-matching.

6. Summary and Discussion of the Previous Literature

The possible explanations of probability-matching behavior reviewed above have connections to each other to some extent. A brief discussion follows.

Otto, Taylor and Markman (2011) compared the two local strategies that can both lead to a global behavior of probability matching: expectation matching and Win-Stay-Lose-Shift strategy. They increased working memory load by giving dual-tasks to some participants, and compared the results with those who were given single-tasks. They claim that increased working memory load would deplete mental resource, thus will influence the use of explicit, rule-based reasoning, and push people to implicit, information-integration strategy. Their results found that both expectation matching and Win-Stay-Lose-Shift strategies are used, but under different

circumstances. The use of either local strategy would lead to the same degree of global probability matching. Table 1 below contains more detailed comparison of these two local strategies.

Table 1. Comparison of Expectation Matching and Win-Stay-Lose-Shift, summarized from Otto, Taylor and Markman (2011)

	Expectation Matching	Win-Stay-Lose-Shift
Working Memory Load	High	Low
System	Explicit	Implicit
Task in this study	Dual-task condition	Single-task condition
Executive resource	Compromised	Intact
Strategy adopted	Integrates long window of previous outcomes	One-trial-back strategy
Self-report Strategy	Cannot specify their strategies	Can specify the Win-Stay-Lose-Shift strategy

Gaissmaier and Schooler (2008) investigated the pattern-search account versus the Win-Stay-Lose-Shift account for probability-matching. They claimed that both accounts are true. For pattern search strategy, it should “go along with higher working memory capacity” (DeCaro, Thomas & Beilock, 2008), while the cognitive shortcut Win-Stay-Lose-Shift strategy should “go along with lower working memory capacity” (West & Stanovich, 2003), as demonstrated in Table 2 below.

Table 2 Comparison of Pattern Search and Win-Stay-Lose-Shift, summarized from Gaissmaier and Schooler (2008)

	Pattern Search	Win-Stay-Lose-Shift
Working Memory Capacity	Higher	Lower
Comment	Could be “smart” if there is a pattern	A cognitive shortcut

James and Koehler (2011) investigated the relationship between expectation generation and probability matching, and concluded that the expectation matching account for probability-matching is in line with the dual-systems account. They believe that expectation matching is the intuition-based part of dual-system, and the sequence-wide expectation serves as source of intuitive appeal of probability matching.

Based on the literature reviewed, pattern search accounts are in general not consistent with dual-system theory. Pattern search requires high working memory capacity, and is an explicit strategy adopted by people that leads to probability matching. However, according to dual-system account, probability matching is a by-product of adopting the intuition-based system, which requires lower working memory capacity than the rule-based system.

James and Koehler (2011) suggested that the prevalence of pattern matching is possibly a U-shaped function of cognitive ability. When the cognitive ability is low, as in animals and young babies, they do not have an expectation of sequence-wide intuition and will not bring interfering history from life, so they do not match with outcome probabilities, while adults do. However, for adults with high mathematical ability, they can override this expectation and find the optimal strategy with careful deliberation or training.

Misconception of Randomness

Studies in cognitive science, mathematical education, and other areas have consistently found that people are not good at understanding randomness. In their judgments about randomness they have problems making the right decision, such as whether a sequence of AABAB is more random than the sequence AAAAA. People are more likely to believe their intuition, and say the first sequence seems more random, but actually both sequences are equally

likely to be produced by a random process that chooses A and B with the same probability. Tune (1964) concluded that it is impossible for the human mind to conceptualize randomness.

Many researchers have found that when generating a random sequence, people also show problems. As early as Reichenbach (1934/1949), it was found that mathematical novices are unable to produce random sequences. Reichenbach found a tendency to overestimate the frequency of alternations between the outcomes. This finding was supported by many later researchers (Bar-Hillel & Wagenaar, 1991; Tune, 1964; Wagenaar, 1972; Budescu, 1987). Griffiths and Tenenbaum (2001) cited Lopes's (1982) research to claim that in producing binary sequences, people alternate with a probability of about 0.6, which is higher than the expected by chance (0.5). This idea is also supported by Wolford, Newman, Miller and Wig (2004), who found that increasing the number of alternations in a sequence raises people's rate of inferring randomness for the sequence. Similar research has reported that over-random sequences (more alternations than predicted by chance) make people more likely to believe that the sequence is random (Ayton & Fischer, 2004; Gilovich, Vallone, & Tversky, 1985).

Researchers have found that people have a difficult time believing the randomness of random events. Hyman and Jenkin (1956) reported that it is easier to convince people that something is structured than random. A similar idea was reported in lottery-related research. Langer (1975) found lottery players have a fallacy, the "Illusion of Control", defined as the "expectancy of a personal success probability inappropriately higher than the objective probability would warrant". In this study, it was found that when lottery players can select their own lottery numbers, they have higher expectations of success.

Kahneman and Tversky (1972) introduced the heuristic that people use to determine the subjective probability of an event, *representativeness*. People determine by judging the degree to

which an event or a sample is “similar in essential characteristics to its parent population”, and the degree to which it “reflects the salient features of the process by which it is generated”. They suggested that irregularity and local representativeness are the two general properties that capture the intuitive notion of randomness. According to their theory, people may be attempting to produce sequences that are representative of the output of a random generating process. Empirical studies had supportive results (Budescu, 1987).

Another perspective that reflects people’s misconception of randomness is research on the fallacies people hold about random sequences. The two most commonly reported and studied fallacies are the *gambler’s fallacy* and the *hot-hand fallacy*. The gambler’s fallacy is the belief that for random events, the occurrence of one outcome will be followed by occurrences of the alternative outcome, i.e., that there is a tendency towards *balance* (Ayton & Fischer, 2004). For example, Heads in a coin-toss event are believed likely to be followed by Tails, according to the gambler’s fallacy. The “hot-hand fallacy” was studied by Gilovich, Vallone, and Tversky (1985). In their study, most people with experience watching or playing in basketball games believe that a player who has just scored several times in a row is more likely to score the next time. However, when these authors computed the sequential dependencies between successive scoring attempts of players, they found that there was no such dependency. Therefore, the players who were believed to be “hot” were not “hot” after all. Actually, players who just had a string of successful scoring attempts are *less* likely to score in the next attempt.

Description-based vs. Experience-based Decision Making

Much research has been devoted to studying probability learning since the 1950's (Tversky & Edwards, 1966; Myers, 1976). Based on those data and theories, researchers now are

carrying out studies on the contrast between description-based decision making and experience-based decision making (Erev & Barron, 2005).

In description-based decision making problems, the outcomes and their associated probabilities are clearly specified to the decision maker. For example, participants are asked to choose between a 70% chance of winning \$10 and a 30% chance of winning \$30. This format of decision problems is commonly used in both economic and psychological research. Mostly, the description-based decision making tasks are “one-shot” decisions (Hertwig & Erev, 2009).

In experience-based decision making problems, the outcome and probability information are not known to the participants, instead, they have to learn this information by experiencing the events. For example, Barron and Leider (2010) gave participants a roulette wheel game where they are asked to select one of the two outcome colors, then are given feedback of the outcome on that occasion. These types of tasks are analogous to a two-armed bandit problem with different payoff distributions associated with the two alternatives.

Considerable evidence has been reported in recent years that decisions from experience and decisions from description can lead to dramatically different choice behavior (Hertwig & Erev, 2009). In description-based decisions, people make choices as if they are overweighting the probability of rare events, as described by prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Empirical evidence exists, for example, that people overestimate the chances of food poisoning (Lichtenstein, et al., 1978) and the chances of lung cancer resulting from smoking (Viscusi, 2002). In contrast, in the case of decisions from experience, people behave as if they underweight the probability of rare events (Erev & Barron, 2005; Hertwig, Barron, Weber, & Erev, 2004). Similar underweighting tendencies are observed in the animal world (Real, 1991).

In random binary prediction tasks, the two types of information source (descriptions vs. experience) were found to lead to different choice strategies. In the description-only version, only one-third to one-half of the participants chose a maximizing strategy (Gal & Baron, 1996; West & Stanovich, 2003). However, in the experience-based version, a much higher proportion chose the maximizing strategy. For example, Hertwig et al. (2004) found that 88% of their participants chose the more likely outcome in their experiment.

Hertwig and Erev (2009) reported the “systematic and robust differences between decisions based on experience and description”, and also provided a review for several causes that have been proposed as contributing to the differences: 1) small sample; 2) recency; 3) estimation error; 4) contingent sampling; 5) information format and cognitive algorithms. However Fox and Hadar (2006) found that "apparent reversal of prospect theory in decisions from experience can be attributed almost entirely to sampling error."

Not many studies have been carried out to investigate description-based decisions when they are repeated. Chen and Corter (2011) investigated people's risk preference in repeated trials of description-based tasks, and found that people do even worse (i.e., fewer expected value maximizing decisions are made) in prospective multiple-trial choice, and in initial trials of a repeated-decisions task with feedback, than in single-trial choice. With enough experience people shift back towards their initial levels of EV-maximization. Newell and Rakow (2007) also used this less common paradigm of repeated trials of a description-based task. They investigated how people combine the two types of information (description and experience) if both are available. They adopted a two-color die with four sides of one color and two sides of another color as the experimental device, instead of a computerized money machine. In this study, they compared people's choice across three different conditions: a description-only condition, an

observation and prediction condition, a combined condition (in which people can infer the outcome probabilities and also experience the trials, with or without feedback), and a “generate sequence” condition.

Newell and Rakow's study had the following findings: 1) for the description and experience combined condition, making predictions has a positive effect on optimal responding, while merely observing does not, perhaps because reflecting on feedback could push the participants toward optimal responding; 2) in the early stage, the combined condition has a lower rate of maximizing than the description-only condition. This negative effect of experience is due to the initial appeal of representative (probability matching) strategies in the trial-by-trial version, when they are trying to outperform the outcome probabilities (West & Stanovich, 2003).

Goals and Decision Making

Goals are often described as the “desirable state of affairs” that people want to achieve through their actions (Osselaer, 2005). In the field of choice and decision making, especially consumer choice studies, researchers have turned from a utility perspective towards goal-based decision making (e.g., Krantz & Kunreuther, 2007). Many researchers have reported theories and results that challenged the traditional multi-attribute utility perspective (Osselaer, 2005). For example, Tversky and Kahneman (1981) found evidence that the utility of specific attributes or attribute levels is not fixed but context-dependent; also, choices are also influenced by other factors such as ease of justification, and avoiding negative emotion (e.g., Simonson, 1989; Luce et al., 2001). Many researchers have started to believe that people's preferences that deviate from multi-attribute utility theory can be explained by a goal-based view of decision making (Carlson et al., 2008).

Kruglanski et al. (2002) gave a theoretical review of goal systems. In their review, instead of treating motivation/goals as a static approach separated from cognition, they support a dynamic approach that views motivation as cognition. They believed that goals or motivations often fluctuate from moment to moment, and different goals can exist at the same time while competing for brain resources. It is also widely believed that people's preferences are constructed in the context of a task, rather than revealed by the task (Krantz & Kunreuther, 2007; Lichtenstein & Slovic, 2006).

In terms of cognitive properties of goal systems, Kruglanski et al. (2002) introduced notions of structural properties and allocational properties. There are a number of variants of goal systems, with different structures and strength of linkage between goals and means. Within a goal system, the units can activate each other (Anderson, 1983, cf. Kruglanski et al., 2002); what is believed to spread between the units are commitment and specific affective qualities “in proportion to the strength of their association”.

A goal could be an explicitly focal goal or a background goal which is unconscious (Kruglanski et al., 2002), but more strongly activated goals are assumed to have stronger impact on behavior (Osselaer, 2005). Krantz and Kunreuther (2007) pointed out that for group decision making the goal is usually explicit, but for individuals it can be implicitly hidden within either conscious or unconscious cognitions and emotions.

Kruglanski et al. (2002) also argued that subconscious goals can be subliminally primed (Bargh & Barndollar, 1996; Nisbett & Wilson, 1977). Osselaer (2005) even claimed that goals can be directly primed, and that exposing people to a subconscious goal can also activate the goal and thus increase its impact on behavior. Empirical evidence (Kruglanski et al., 2002) has shown that when people are primed with a goal corresponding to one that is currently pursued,

then their reaction time to identify means for this goal is significantly shorter than if the prime is a non-goal control.

Goals can change with contextual framing in their shape and form. Active means to realize a goal can also be different according to contexts. Also, substitutability relations between different means can be context-dependent (Kruglanski et al., 2002; Carlson et al., 2008).

Osselaer (2005) concluded that the influence of goals on behavior is largely “variable, highly context-dependent, and heavily subject to processes of learning and forgetting”.

The “allocational properties” of goal systems refers to the fact that goals compete for limited mental resources (Kruglanski et al., 2002). This idea implies that currently active goals may “pull resources away from each other”, and mutually hinder their attainment. Different *means* to the same goal may also compete with each other for mental resources. It has also been demonstrated that priming alternative goals undermines commitment to the focal goal (Shah & Kruglanski, 2002). Another related idea is that heterogeneous goals make construction of preferences difficult (Krantz & Kunreuther, 2007).

In terms of the motivational properties of goal systems, Kruglanski et al. (2002) pointed out that human action is goal-driven to a large extent, and it could result in either success or failure. Moreover, when pursuing a goal, people determine how committed they should be, by estimating the utility or value of the goal and the expectancy of attainment of the goal. They concluded that goal commitment is a “multiplicative function of value and expectancy”, however, the weights can vary depending on specific goal and/or individual.

Chen and Corter (2011) investigated people's preference between sure gain/loss and risky gain/loss in repeated trials of description-based decision making. Asymmetric learning rates were found for the gain and loss domains, in that in the loss domain, people learned faster to adopt an

optimal strategy that maximizes the expected value. The interesting phenomenon is that in the self-reported strategies, people who chose the non-optimal risky loss claimed a reason of trying to completely "avoid loss". This is an example of an unrealistically high goal (experiencing no loss) leading to a non-optimal strategy and result (choosing the risky loss option which has a lower expected value).

Pragmatic Reasoning Schemas

Cheng and Holyoak (1985) proposed the idea of pragmatic reasoning schemas. A pragmatic reasoning schema is a set of knowledge structures, learned by experience, consisting of “generalized, context-sensitive rules” defined in terms of classes of goals and relationships to the goals. This view assumes that people reason based on abstract knowledge structures induced from daily-life experiences, such as permissions and causations, in contrast to previously proposed formal approaches to reasoning, such as syntactic context-free rules of inference, and to generalization-free memories of specific experiences.

The idea of pragmatic schemas has been applied to many types of reasoning, such as hypothesis testing, deduction reasoning, induction reasoning, etc., and has been proved to be helpful for people's reasoning performance. One famous example is Wason's selection task (Wason, 1966; Wason & Evans, 1975), in which people need to verify a statement by induction from the results of examining two cases, and attempt to decide what additional information is necessary to complete the task. It has been found that when the selection task is framed under concrete contexts, people's reasoning performance is dramatically better than in abstract contexts (Evans, 1982). In a reasoning task about postal-service incidents, Johnson-Laird et al.(1972) found a sharp contrast between performance under two types of contexts: 15% correct in an abstract context, and 81% correct in a concrete context. Unturbe and Corominas (2007)

mentioned that an abstract task “which is free of contextual cues would be required for assessment of the rule-generating ability”.

However, pragmatic schema are not always available to facilitate people's reasoning performance. For example, an arbitrary rule that is not related to ordinary life experiences does not necessarily evoke any reasoning schemas (Cheng & Holyoak, 1985). When people failed to interpret the arbitrary rule in terms of a reasoning schema, they would have to turn to formal reasoning. Moreover, Noveck et al. (1991) argued that errors on reasoning tasks do not equal to lack of competence, instead, they could result from either “lack of sophistication with reasoning strategies that follow from metalogical analysis”, or from “the application of pragmatic principles to problems that violate pragmatic principles”.

Chapter III STUDY ONE

Introduction

This section introduces the research question, methodology and results of Study One. A brief discussion is also included. Study One investigated if presenting the binary prediction task to the participant as involving prediction of *sequences* rather than predicting repeated individual trials, and rewarding perfect performance for sequences, tends to elicit more probability matching. Such a finding would support the hypothesis that participants' attempt to achieve perfect prediction of a sequence of outcomes may be one cause of probability matching. Study 1 manipulated two task factors. One factor is the nature of the rewarded performance goal (perfect prediction of a *sequence* of trials or correct prediction of *individual trials*), and the other factor is the probability "bias" of the events defined in the prediction tasks, with the probability of the more likely event or outcome being set either at 75% (bias) or 50% (no bias). Previous studies of probability matching have not included a condition in which the binary outcomes are equally likely, because in this condition there is no maximizing strategy, thus probability matching strategy cannot be characterized as an inferior strategy. We include this condition to also assess generalizability, specifically whether predicting sequences rather than single outcomes can produce more matching behavior in a prediction task that more closely resemble those discussed by Kahneman and Tversky (1972).

According to Tversky and Kahneman's (1971) *representativeness heuristic*, people tend to generate random sequences similar to the perceived typical or "representative" random sequences, meaning with no noticeable patterns, with the probability of each outcome proportional to its specified probability. We believe that when people have an unrealistically high

goal in binary prediction tasks they tend to adopt the representativeness heuristic, and allocate their predictions proportional to the given probabilities of the outcomes, thus showing probability matching. On the other hand, when the perfect-performance goal is not implicitly adopted nor emphasized by the task demands, people may be less obsessive about matching the percentage of their predictions to the given probabilities, and thus adopt the maximizing strategy more often.

Our specific hypotheses are that: 1) In the bias (75%) condition, learning of the maximizing strategy would be observed across trials and sets of trials, however, in the no-bias (50%) condition, since there is no optimal strategy, no significant change of overall strategy use is expected across the trials; 2) If the decision maker is reinforced (with bonus pay) for each correct *single-trial* prediction, then the advantage of the maximizing strategy may be more easily learned. If, on the other hand, predicting the *sequence* over four-trial sets is emphasized (by giving bonus pay only for perfect prediction of all four trials in each set of trials), this may encourage the non-optimal probability matching strategy.

Method

Design

In Study 1, we investigated two possible factors affecting the use of a probability matching strategy. One factor is the way the prediction goal is specified, or the aspect of the outcomes emphasized to the decision maker, and the other factor is the probability bias of the events defined in the prediction tasks. Each of the two factors has two levels: the *aspect* of outcomes emphasized compared an emphasis on single trial prediction with an emphasis on predicting *sequences* of four-trial sets. The reason for this manipulation is that it may be that

people tend to adopt the sub-optimal matching strategy because they implicitly adopt the inappropriate (because unrealistic) goal of predicting *perfectly* across the n trials of the task. We assumed this manipulation to be effective because in prospective multiple-trial choice tasks, Chen and Corter (2006) found that people do even worse (less expected value maximizing decisions are made) than in single-trial choice conditions. The probability bias factor also has two levels, with the probability of the more likely event or outcome being set either at 50% or 75%. So this study is a 2x2 factorial between-subjects design, with four conditions in total (sequence_bias, sequence_no-bias, single-trial_bias, single-trial_no-bias)

In this study, participants were asked to predict the color of a light, which randomly showed the color of red or green when turned on, by clicking on the buttons presented on an interface developed by the researcher. In order to counterbalance any effects of color preference and position preference in the task, we counterbalanced conditions. The following Table 3 shows the counterbalancing of payoff colors and positions, and it is the same for both single-trial and sequence conditions .

Table 3. Illustration of Counterbalanced Conditions in Study 1

Probability Bias	Left Button		Right Button	
	Color	Probability Bias	Color	Probability Bias
No-Bias 50% - 50%	Red	50%	Green	50%
	Green	50%	Red	50%
	Red	50%	Green	50%
	Green	50%	Red	50%
Bias 25% - 75%	Red	25%	Green	75%
	Green	25%	Red	75%
	Red	75%	Green	25%
	Green	75%	Red	25%

Participants

The experiment was conducted on Amazon’s Mechanical Turk (AMT) worker marketplace, therefore participants were registered Amazon Mechanical Turk worker, who self-select to work on our experiment on their own time (in exchange for modest payments), after our task was “published” on AMT and before it expired. We took care that each participant performed the task only once by specifying in our instructions that each participant can only do this task only once, and subsequent task completions by a single worker would not be accepted (meaning no payment would be given). All workers who had participated in the task once were blocked, so that we can prevent duplicate workers for any task. The total number of participants tested was 350, yielding roughly 90 participants in each cell of the 2 x 2 design, as shown in Table 4 below. This resulted in a total of 175 participants in the no-bias conditions and 175 in the bias conditions.

Table 4 Number of Participants in Each Condition of Study 1

	Single Trial	Four-trial Sequence
No-bias	N = 88	N = 87
Bias	N = 88	N = 87

As in other typical samples of AMT workers, participants were relatively diverse: their mean age was 30.9, and ranged from 17 to 64. Participants were 46% male and 54% female. In college, 26.9% majored in Math/computer science/information systems/engineering, 26.8% majored in the natural or social sciences, and 46.5% majored in other subjects or none; 58.6% had taken at least one statistics course. 81.7% of the participants were native English speakers, and other participants’ native languages included Arabic, Chinese, French, etc.

The participants were randomly assigned to one of the conditions of this study, thus should be evenly distributed among conditions, as shown in Tables 3 and 4. The task took about

6 minutes to complete. Participants were paid \$0.25 as the base pay for participating in the study, plus a performance-based bonus payment (averaging about \$0.75). In the single-trial conditions, they earned \$0.01 for each *trial* that they predicted correctly, and in the four-trial “sequence-prediction” condition, they received a bonus of \$0.10 for each of the *4-trial sequences* that they predicted perfectly.

Procedure

In this experiment, participants were asked to complete a prediction task for a series of random binary events, working with an interface developed by the experimenter and embedded in Amazon's Mechanical Turk. The program was developed by using the HTML language with embedded JavaScript.

Upon starting the task, participants were randomly assigned to one of the four conditions (sequence_bias, sequence_no-bias, single-trial_bias, single-trial_no-bias). They were then shown the main interface screen, with instructions printed at the top of the screen. In the middle of the display screen, there was a picture of the light that showed the color of red or green randomly on each trial according to the specified probability. To the left or right side of the light, there were buttons labeled “red” or “green”. By pressing one of the buttons on each trial, participants can make their predictions. Under the prediction section of the screen was the feedback section, which automatically reported (in words) the actual color of the light after the participant made his or her prediction, as well as the amount of bonus they won.

Figure 1 and Figure 2 show the layout of the interface screens for single-trial conditions and four-trial set conditions. In the counterbalanced study, the positions of the two buttons (Red

Light or Green Light) and the payoff probabilities of the outcomes were opposite in order to counterbalance the button-position effect.

In the instructions, participants were told that the color of the light was selected randomly, and they were also be informed of the probability that it shows the color green or red on each trial. Then they were asked to predict the color of the light, either in the next single trial or in the next set of four trials.

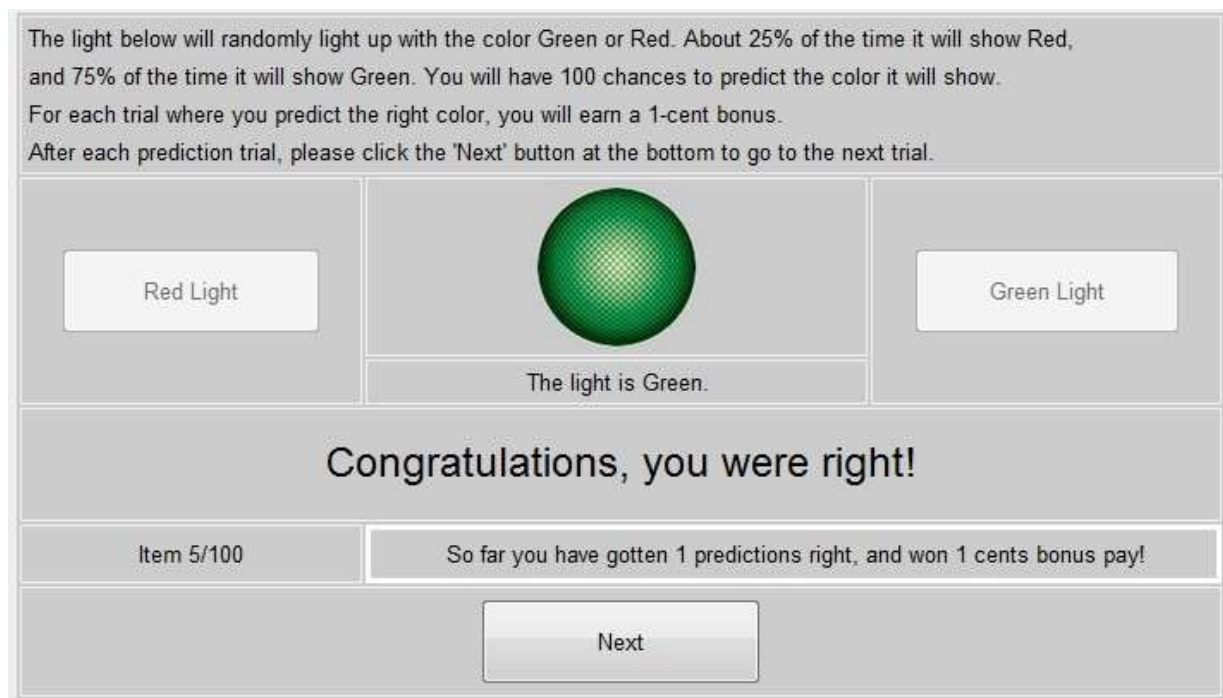


Figure 1 Interface for Single Trial Prediction Tasks

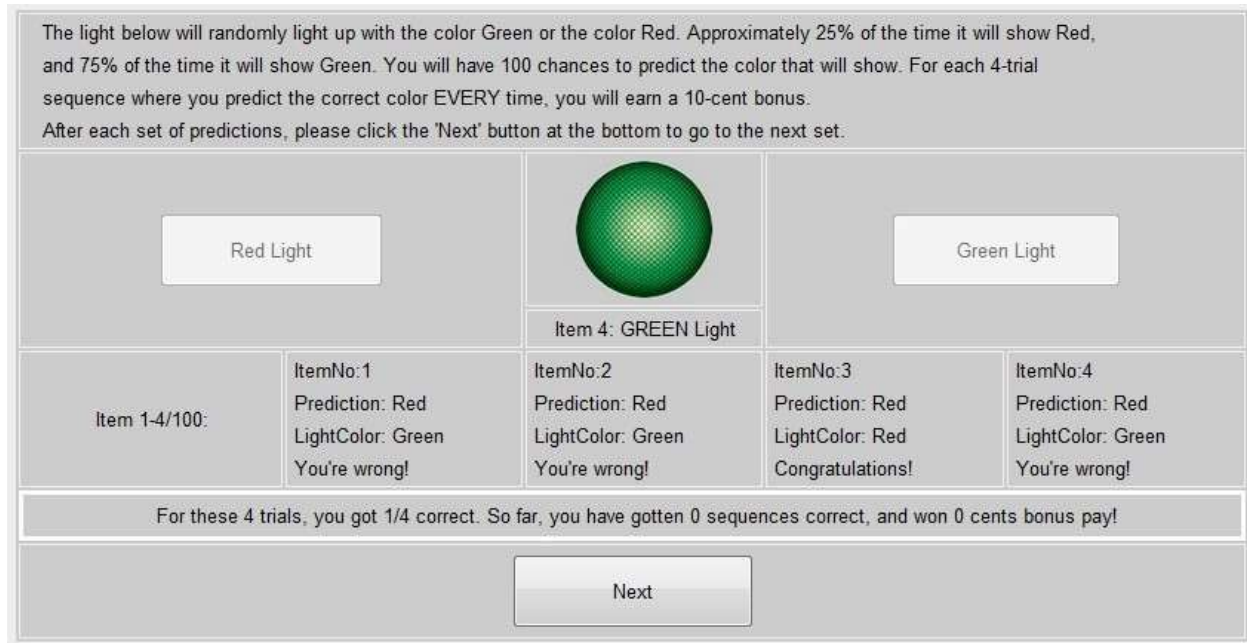


Figure 2 Interface for Four-trial Set Prediction Tasks

In the single-trial prediction conditions (single-trial_bias, single-trial_no-bias), participants experienced 100 individual trials, making their prediction and receiving feedback on each trial. Participants made a prediction by clicking on either the red or the green response button. Feedback as to the actual obtained color of the light for that trial then appeared at the bottom of the screen. A bonus of \$0.01 was given for each correct prediction; thus, each participant in the no-bias (50%-50%) condition could expect to earn approximately $(1/2)(.01)(100) = \$0.50$ in bonus pay. In the bias (75%-25%) condition, expected payoff of course depends on the proportion of maximizing choices (i.e., on the strategy used) by the participant, with an expected value of \$.625 for a probability matching strategy and \$.75 under maximizing.

In the four-trial sequence condition, there were also 100 trials, but these were presented to participants as 25 four-trial sets. In each of the sets, they were asked to predict the colors of the light on all four trials, and were informed that they would earn the bonus only if they correctly

predicted the outcomes for all four trials in the sequence. In this condition, a set of four boxes near the bottom of the screen represented the four trials, and the participant clicked on the red or green button for each trial, filling in the boxes sequentially. Feedback as to the obtained color of the light for each trial was also given sequentially for the four trials, with about 0.3 seconds between presentations of each trial's outcome. Outcome feedback for all four trials remained on the screen while feedback as to any payoff bonus for the sequence was added. A bonus of \$0.10 was given for correct prediction of each sequence, thus participants in the no-bias (50%-50%) condition could expect to earn approximately $(1/16)(.10)(100) = \$0.625$ in bonus pay. Expected bonus pay in the bias (75%-25%) condition again depends on the proportion of maximizing choices (i.e., on the strategy used) by the participant: $(.1526)(.1)(25) = \$0.382$ if one uses matching strategy for the entire task and $(.316)(.1)(25) = \$0.790$ if the maximizing strategy is used for the entire task.

After the prediction and feedback session as described above, the participant needed to click the button labeled "Next" to proceed to the next trial or the next set of four trials.

After completing all the prediction trials, each participant was asked to complete a questionnaire about their prediction strategies. The questionnaire also requested demographic information, including gender, age, math ability and educational background.

Results

In this study, participants were asked to predict the color of a light that randomly shows the color of red or green, for 100 trials. In the single-trial condition, participants were asked to predict the color trial by trial, and in sequence condition they predict the colors of four trials at one time as a set (25 sets). The probability of the two options are either equally likely (no-bias) or not (bias), and in the bias conditions, the probability of the more likely option is 75%.

The participants' predictions were recorded, with 1 representing the choice of the more likely color and 0 representing the less likely color in the bias condition; and since there is no optimal choice in the no-bias condition, we used 1 representing the color of red, and 0 representing green. The data analysis method and results are introduced in the following part of this section.

As an indicator of strategy adoption, we calculated the total proportion of participants who chose maximizing strategy or probability matching strategy in the 4-trial sets respectively for each experimental condition, as shown in Figure 3, Figure 4, and Figure 5. Our main hypothesis was that participants would more often exhibit pattern-matching when prediction of sequences was rewarded rather than prediction of single-trial outcomes. In order to test this hypothesis, we coded the strategy used by a participant in each set of four trials, regardless of condition. In the bias (75%) conditions, we scored the responses for a set of four trials as consistent with probability *maximizing* if all four responses were predictions of the more likely option, and as probability *matching* if exactly three out of four predictions were of the more likely option. In the no-bias (50%-50%) condition, we scored the responses as consistent with probability matching for a 4-trial set if the participant generated a mixed sequence with exactly two predictions of red and two of green. Graphs of the proportion of matching across sets for the no-bias and bias conditions are given in Figure 3 and Figure 4.

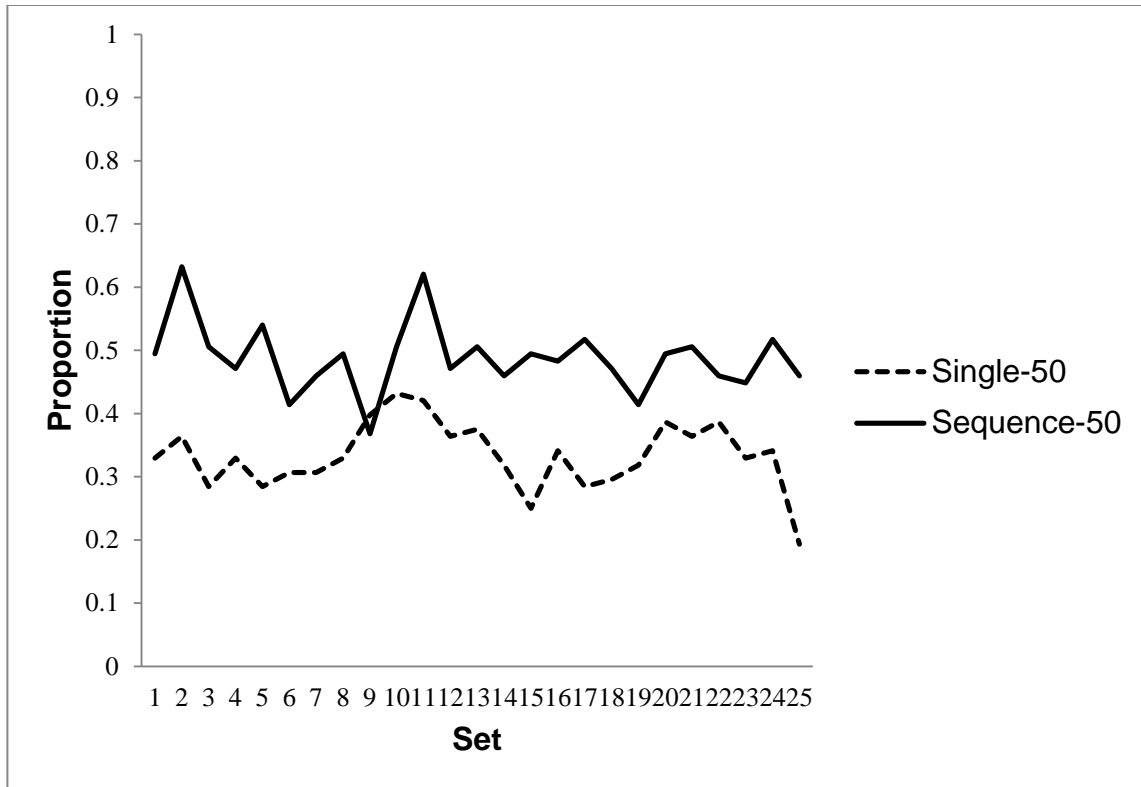


Figure 3 The proportion of participants using probability matching strategy, for no-bias conditions (single-trial and sequence conditions)

Figure 3 shows that in the no-bias (50%) conditions, probability matching behavior is more prevalent in the sequence condition than in the single-trial condition. This difference was confirmed using a generalized linear mixed model to analyze the binary data for the 25 sets (or pseudo sets, in the single-trial condition), with 1 representing a choice of probability matching strategy and 0 representing not choosing the corresponding strategy. The covariance structures is assumed to be AR(1), assuming that the prediction at time point $t+1$ is correlated to the prediction at time point t .

The main effect of Goal Type (sequence or single-trial) was significant, $F(1, 173)=74.62$, $p < .001$. It can be observed from Figure 3 that in the no-bias (50%) conditions, there is more probability matching behavior in the sequence condition than in the single-trial condition. This

result confirms our hypothesis that when perfect prediction of a sequence of outcomes is the explicitly rewarded goal, people are more likely to match predictions in proportion to the probability of the random outcomes. The effects of Sets and the Sets x Goal Type interaction were not significant, $F(24, 4152) = 1.35$, $p=.12$, and $F(24, 4152) = .94$, $p=.55$, respectively. This is also consistent with our expectation that in the no-bias conditions, no dramatic change of probability matching strategy overall should be observed in the no-bias conditions, and that the changing profile should not be different between the single-trial and sequence conditions.

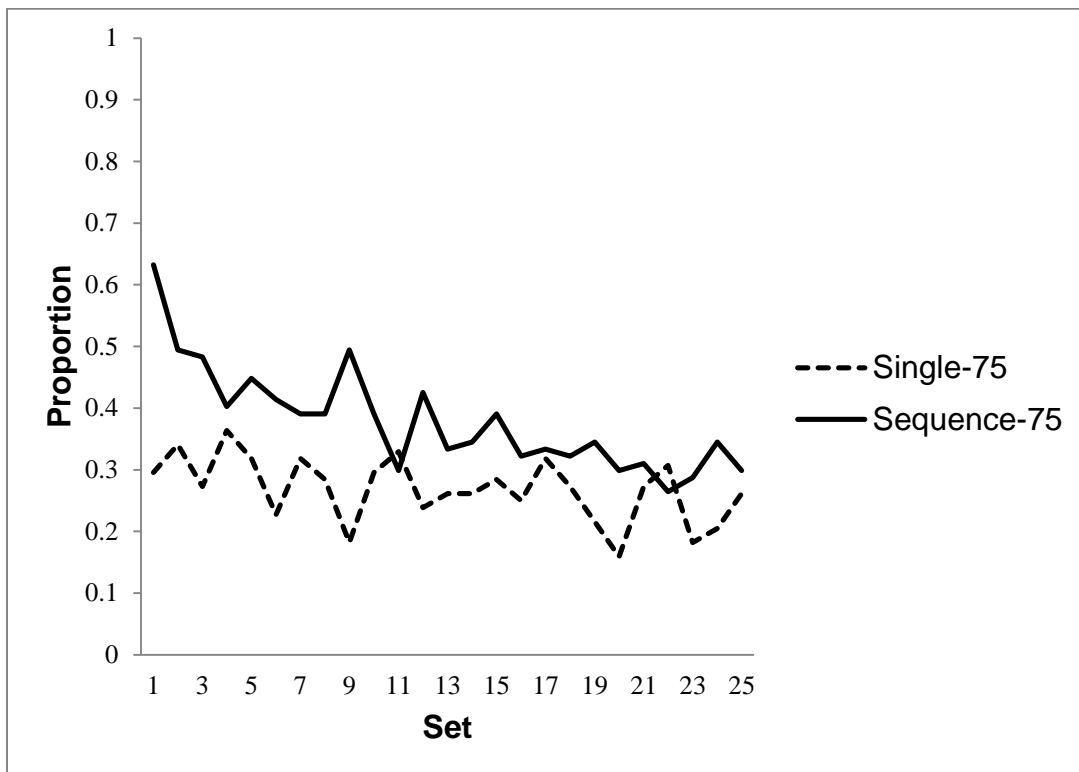


Figure 4 The proportion of participants using probability matching strategy, for bias conditions (single-trial and sequence conditions)

In Figure 4 above, it is shown that in the bias (75%) conditions, people are initially more likely to choose a probability matching strategy in the sequence condition than in the single-trial condition, however, they learn to abandon this strategy toward the end of the experiment. The

main prediction is again confirmed: respondents in the sequence condition exhibit more probability-matching than do participants in the single-trial condition. This effect was demonstrated using a generalized linear mixed model. In this analysis the main effect of Goal Type was significant, $F(1, 173) = 37.89, p < .001$. The main effect of Sets was also significant, $F(24, 4152) = 1.71, p = .017$, suggesting that the profiles are not flat in general. As shown in Figure 4, this effect might be due to the decrease from the initial sets to the ending sets in the sequence condition. Also, the Sets x Goal Type interaction is significant, $F(24, 4152) = 1.64, p = .025$, demonstrating that the profile of responses across sets differs for the two goal conditions. It seems from Figure 4 that the main difference lies in the initial trials more than in the ending trials. Since the sequence condition had an especially high initial level of matching, it is not surprising to find a more dramatic drop in this condition than in the single-trial condition.

This apparent decline in probability-matching behavior across trials in the bias conditions is accompanied by an increase in probability maximizing. Figure 5 shows the proportion of subjects choosing the maximizing strategy across sets in the bias condition. There is more maximizing strategy observed in the single-trial condition than in the pattern condition, consistent with our hypothesis. The proportion of choosing maximizing strategy for the no-bias conditions is not analyzed, because “maximizing” does not make sense for equally likely events.

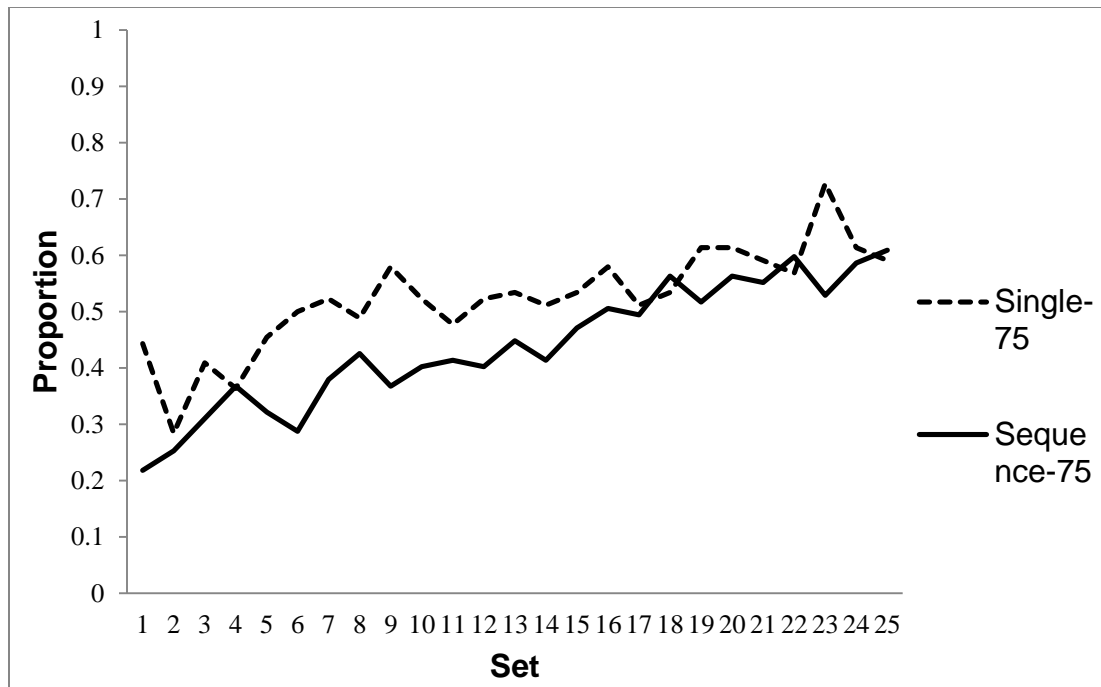


Figure 5 The proportion of using maximizing strategy, for bias conditions only (single-trial and sequence conditions)

As Figure 5 above shows, in the bias (75%-25%) conditions respondents in the single-trial condition exhibit more maximizing than do participants in the sequence condition. This effect was confirmed in a generalized linear mixed model. In this analysis the main effect of Goal Type was significant, $F(1, 173)=14.26$, $p\text{-value} < .001$. The main effect of Sets was also significant, $F(24, 4152) = 3.28$, $p\text{-value} < .001$, with the pattern shown in Figure 5 above suggesting a significant increase of maximizing strategy use overall. However, the Sets x Goal Type interaction was not significant, $F(24, 4152) = 1.37$, $p = .11$, indicating a roughly parallel profile plot between the two conditions.

Figure 6 and Figure 7 contrast the distribution of responses probabilities for the first 20 trials and the last 20 trials in the four conditions, for each 4-trial set of trials (in the pattern conditions) or pseudo-sets of 4 trials (in the single-trial conditions). In the bias (75%) conditions

the response probabilities are defined as choosing the more likely outcome; in the no-bias (50%) conditions, the response probabilities are defined in terms of the outcome Red.

Figure 6 below (panels a, b, c, d) presents results for the no-bias (50%) conditions. This probability is distributed with a median around 50% representing matching behavior, both in the first 20 trials and the last 20 trials, although some tendency to prefer Green over Red is observed. There is also more probability matching in the sequence conditions (for both the first and last 20 trials) than in the single-trial conditions

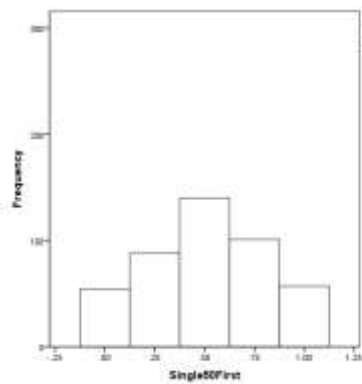


Figure 6a. First 20 trials for single-trial, no-bias condition

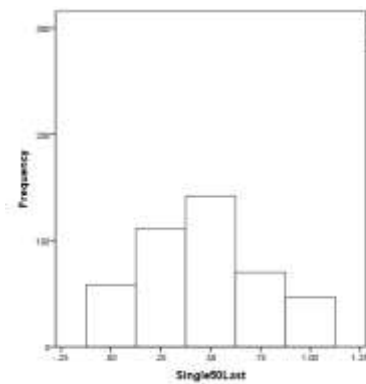


Figure 6b. Last 20 trials for single-trial, no-bias condition

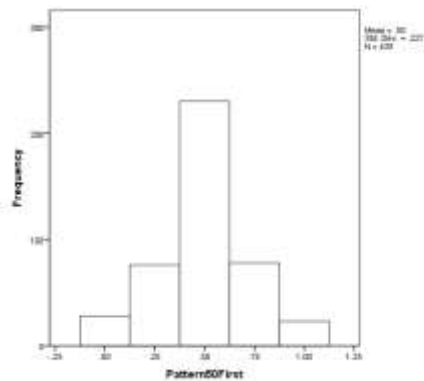


Figure 6c. First 20 trials for sequence, no-bias condition

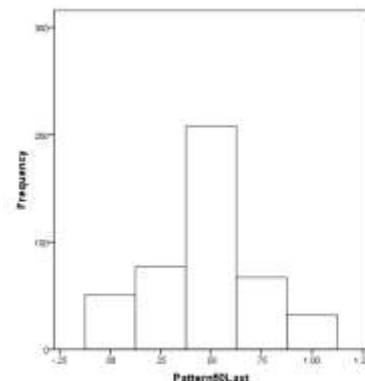


Figure 6d. Last 20 trials for sequence, no-bias condition

Figure 6 The distribution of individuals' probabilities over the first 20 trials (left panels) and last 20 trials (right panels) of choosing the red light in the no-bias (50%) condition.

Figure 7 below provides the same information as Figure 7 for the bias (75%) conditions. In the first 20 trials, there is more probability matching behavior in the sequence condition than in the single-trial condition. However, in the last 20 trials, the predominant strategy is maximizing in both conditions. This indicates that strategy learning did occur in both conditions, and it is more effective in the sequence condition.

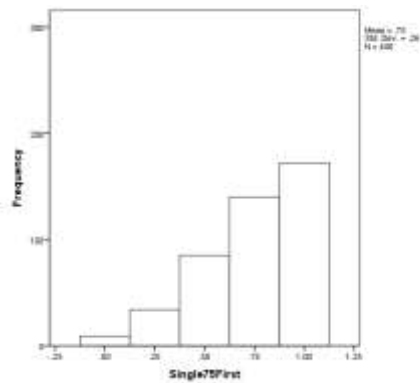


Figure 7a. First 20 trials for single-trial, bias condition

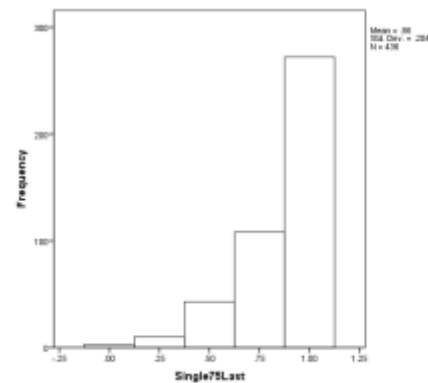


Figure 7b. Last 20 trials for single-trial, bias condition

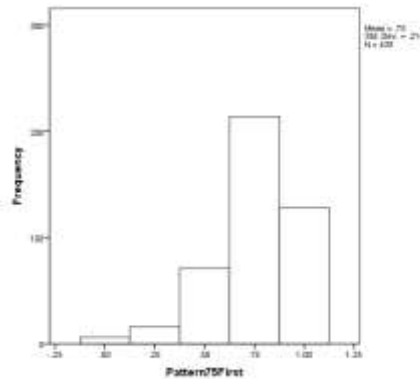


Figure 7c. First 20 trials for sequence, bias condition

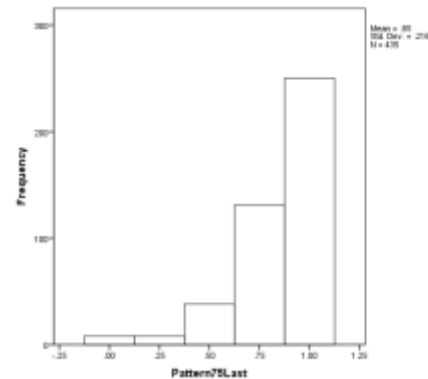


Figure 7d. Last 20 trials for sequence, bias condition

Figure 7 The distribution of individuals' probabilities over the first 20 trials (left panels) and last 20 trials (right panels) of choosing the more likely outcome in the bias (75%) conditions.

Comparing Initial Tendencies:

The mean of the proportion of participants using the probability matching strategy in the first two blocks (20 trials) are compared between the single-trial and sequence groups, in both bias and no-bias conditions. The results show that the means are significantly different for no-bias condition $F(1, 173) = 19.06$, $p\text{-value} < .001$, and for bias condition $F(1, 173) = 20.10$, $p\text{-value} < .001$, indicating that people are more likely to employ probability matching strategy in the sequence conditions than in the single-trial conditions in the initial trials.

Discussion

This study demonstrates that participants exhibit more probability matching behavior when the prediction task is presented as involving predicting sequences of trials rather than individual trials, and when perfect prediction of a payoff string is required to earn a performance bonus. The payoff scheme in the present sequence condition paid a \$0.10 bonus for perfect prediction of a four-trial sequence, presumably affecting the goals participants adopt in the task.

Probability-matching behavior was observed in the no-bias (50%-50%) condition as well as in the bias (75%-25%) condition. Even in this no-bias condition probability matching was more prevalent when attempting to predict sequences compared to predicting the outcome of single trials. In this no-bias condition differences in predicted outcome strings between the sequence and single-trial conditions cannot be attributed to differences in rewards or in the speed of learning to maximize. Rather, they must reflect differences in prediction strategy when participants focus on sequences versus single-trial outcomes (c.f. James & Koehler, 2011). As noted by Kahneman and Tversky (1972; see also Tune 1964; Wagenaar, 1972), there is a bias in how participants perceive randomness in sequences of coin flips, such that they judge mixed

outcome sequences (e.g., HHTHT) to be more likely than pure outcome sequences (e.g., HHHHH). According to Kahneman and Tversky, participants make this error because they use a representativeness heuristic, judging the mixed sequences as more likely because they more closely resemble a mental prototype of a random string.

In contrast, probability-maximizing was more prevalent in the single-trial condition. In all conditions, the prevalence of maximizing behavior increased across trials. This demonstrates that one effect of experience (with outcome feedback) is to increase rational behavior, even in description-based prediction tasks (cf., Newell & Rakow, 2007; Chen & Corter, 2012). In description-based tasks, people are generally found to overweight the probability of rare events, leading to more irrational choices.

The group-level data from our participants showed a very slight trend of “undermatching” (i.e., slightly less than 75% predictions of the more likely outcome) in the first block of the bias (75%-25%) condition, with overmatching emerging across the later blocks. While undermatching and overmatching can be predicted by certain reinforcement learning models (Herrnstein, 1961; Baum, 1979), for the present description-based decision task we prefer to interpret these findings as suggesting that participants are trying a mix of strategies, since analysis of individual-level data shows that participants indeed show a mix of strategies in all blocks. Note that above we operationally defined probability matching (for the bias condition) as when the participant shows 3 out of 4 predictions of the more likely event, and probability maximizing as all four predictions being the more likely event. Additionally, we can define a prediction sequence with 2 reds and 2 greens as reflecting a naïve 50%-50% split of responses. Undermatching can then be understood as resulting from a mix of such “naïve” prediction sequences and probability matching (or maximizing), and overmatching as resulting

from a mix of maximizing and matching strategies. Interestingly, the naïve 50%-50% strategy not only becomes less common across blocks of trials, but is less common overall in the sequence condition compared to single-trial predictions. This might be attributed to a stronger effect of representativeness in the sequence condition. Note that for human subjects observed overmatching in a *single* participant's responses may reflect switching between strategies; when observed in group data, it may merely reflect inter-individual variability in preferred strategy (Estes, 1956; Shanks, Tunney & McCarthy, 2002).

To summarize, the results of Study 1 seem to confirm the hypothesis that explicit or implicit adoption of perfect prediction goals (as promoted by the sequence condition) are one cause of probability matching behavior. However, the objection could be raised that the single-trial and sequence conditions of this study differ in *two* important respects: not only does the sequence condition manipulate goals by rewarding perfect prediction of 4-trial sequences, it also differs by *grouping trials* into sequences in the first place, making the strings of observed and predicted outcomes more salient. James and Koehler (2011) argue that an emphasis on sequences rather than individual trials is one important determinant of probability matching, because it makes the expected frequencies of the observed or predicted outcome strings more salient, promoting expectation matching. Thus, it is not clear if the increased matching in our sequence condition stemmed from emphasizing prediction of sequences, or from promoting the perfect prediction goal by explicit rewards.

Furthermore, since maximizing behavior seems to increase with experience (i.e., across trials) in this study, there is another possible concern involving the frequency of feedback. Specifically, it is possible that reinforcement of correct predictions at the sequence level (that is, every four trials rather than every trial) might lead to less efficient strategy learning, slowing the

abandonment of probability matching in favor of maximizing. However, we took great care to make sure that the two conditions were equivalent as learning experiences. First, the participant made predictions for all four trials of a sequence sequentially, and feedback was also given sequentially, with each trial's actual outcome being revealed in turn. Thus, the two conditions are designed to be as equivalent as possible in this respect.

However, to exclude the possibility that mere trial grouping (prediction of individual trials versus prediction of sequences) might be the critical determinant of increased probability matching in the sequence-prediction condition, we designed a second study that manipulated goal type while holding all other aspects of the task constant.

Chapter IV STUDY TWO

Introduction

We believe that in order to try to achieve perfect performance in a simple prediction task (SPT), people are more likely to generate a sequence that they believe is *representative* of a random binary sequence, because intuitively, people believe that similarity or having the predicted string "look right" is a necessary condition for perfect prediction of a sequence. In contrast, a maximizing strategy generates a sequence consisting of all the same elements, thus it does not satisfy the necessary condition of being "representative". The paradox is that the maximizing strategy *seems* to have a lower probability of predicting perfectly than the probability matching strategy (to the naïve participant), although actually it is higher. For example, in a sequence with 10 trials, where in each trial the probability of event A is 80%, using a maximizing strategy will result in a 10.7% chance of predicting perfectly, but a probability matching strategy has only a 0.65% chance of predicting perfectly. Thus, adopting a more realistic goal (lower than perfect) may lead people away from being obsessive with probability matching, towards maximizing.

Fantino and Esfandiari (2002) investigated this idea that probability matching may arise from having an implicit goal of perfect prediction, but did not find a significant result when they tested this hypothesis. In our study, the manipulation and study design will be different. In this study, we mainly want to test whether the goal of prediction plays a role in people's choice of strategy. We believe that setting an unrealistically high goal (e.g., predict a binary random sequence of n trials perfectly), whether it is set implicitly by the participant or explicitly by the experimenter, will lead to more probability matching behavior, whereas a goal that is more

realistic (achieve relatively good prediction such as 70% correct) may yield more use of a maximization strategy.

In Study 1 this idea was investigated. However, in that study it was confounded with the sequence versus single-trials manipulation. Study 2 investigated if setting an unrealistically high goal alone can lead to more probability matching behavior, compared to a goal that is more realistic. In this study participants were asked to predict the color of a light which shows red or blue randomly, for five 5-trial sets (i.e., 25 trials in total). The probability of the more likely event was equal to .8. The experimental factor manipulated between subjects was Goal Level, which refers to three levels of performance participants had to achieve in order to earn bonus pay for a given set. These three levels are termed “perfect goal” (100% correct predictions in a set of five trials), “medium goal” (at least 80% correct), and “low goal” (at least 60% correct). Our hypothesis is that probability matching behavior will be more prevalent in the perfect goal condition than in the low goal and medium goal conditions.

Method

Design

In this study, the task was predicting five 5-trial sequences of a random binary sequence in advance, with outcome feedback after each sequence. In each trial, the probability of showing blue was 80%. We also had counterbalanced conditions where the probability of showing blue was 20%, and showing red was 80%.

To manipulate the levels of goals, we had different payoff policies for different conditions. The payoff policies were: getting a \$0.15 bonus if they predicted 60% of the trials in a sequence, 80% of the trials in a sequence, or all five trials perfectly, respectively. Participants

were randomly assigned to one of the three conditions, and they were given different instructions in terms of their goal and payoff policy.

As a manipulation check, we asked people about their goals. They were also asked about the strategies they used when making the predictions, and whether their strategies would change if they do this task again. In addition, we asked participants to evaluate their own performance, and also to estimate the average performance of other participants in the study (to examine the perceived difficulty of the task). The main idea is to compare the behavior of people having different levels of imposed goals, to see if those who are in the unrealistic goal group used a probability matching strategy more than those who are in the moderate or realistic goal groups.

Participants

As in Study 1, participants were recruited from Amazon's Mechanical Turk (AMT), where registered users select the tasks that they want to participate in. We specified in the description of the task that participants can only do the task once, and subsequent task completions would not be accepted. All AMT workers who had participated in the task were blocked, to prevent duplicate workers. This prohibition included not allowing participation in Study 2 for those who had participated in Study 1. The task took about 5 minutes to complete.

The participants were randomly directed to one of the three conditions of this study, and were evenly distributed among conditions, as shown in Table 5 on the next page.

A total of N=300 workers participated in the study. The mean age of participants was 30.70 years, with a range from 17 to 68. The sample was 61% male and 39% female. Academic preparation was diverse: 13.7% majored in Humanities in college, 29% had majored or were majoring in Math/computer science/information systems/engineering, 21.3% majored in the

natural or social sciences, and 36% reported majoring in other subjects or none; 55.4% had had at least one statistic or decision-making course in college. English was the native language for 70.6% of our participants. Participants were paid \$0.25 as the base pay for completing the study, plus a performance-based bonus payment as defined earlier in this section.

Table 5 Study Design and Number of Participants in Each Condition of Study 2

Specified goal and payoff	Light Shows Blue	Light Shows Red
	80%	80%
60% Correct with Normal Bonus	N = 50	N = 50
80% Correct with Normal Bonus	N = 50	N = 50
100% Correct with Normal Bonus	N = 50	N = 50

Procedure

In this experiment, participants were asked to complete a prediction task of a series of random binary events. Upon entering the task, they were randomly directed to one of the conditions, and received instructions according to the condition they were assigned to. Mainly, the instructions let them know the background story of the study: that the light would randomly show the color blue or red, with probabilities of the two outcomes specified. They were also notified of the payoff policies according to the goal of their tasks.

After reading the instructions, participants were told to predict the color of the light for the next five times when it is turned on. The interface used for Study 2 was essentially that used in the sequence conditions of Study 1, but using 5-trial rather than 4-trial sets. The participants' task was to predict five-trial sequences of a random binary sequence in advance, with outcome feedback after each sequence. As in Study 1, participants were asked to predict the color of a light, which on each trial was randomly selected to be either blue or red. On each trial, the probability of one color showing was .8, while the probability of the other color showing was .2.

After predicting one sequence of 5 trials, participants received feedback for the sequence (shown the actual colors of the past five trials, and were also informed in words whether their prediction satisfied the goal of the task and the amount of bonus they won), and then were asked to predict another 5-trial sequence of the same random event. There were five sequences in total.

Goals were manipulated by specifying different payoff policies to different groups of participants. The conditions differed only in the performance goal that would lead to a bonus payment for each set of five trials. In the low-goal condition participants need to correctly predict 3 out of 5 trials (60%) to earn the performance bonus; in the “medium goal” condition the rewarded level was 4 out of 5 (80%) correct and in the perfect-goal condition 5 out of 5 (100%) correct predictions were required. In all conditions participants received a \$0.15 bonus if they met the specified prediction goal. Participants were randomly assigned to one of the three conditions.

After the prediction task, all participants were asked to complete a questionnaire about their strategies of prediction. It also collected their demographic information, such as gender, age, mathematics ability and education background.

The questionnaire also included the following questions:

1. What strategy did you use to make your predictions?
2. Did you change your strategy during the task? If yes, in what way?
3. If you did the prediction task again, would you change your prediction strategy? If yes, in what way?
4. How likely it is for you to win the bonus if you do this task again?
5. What are you participating this study for (please check all that apply)?
 - a. For the payment, especially the bonus

- b. For the base pay, I didn't try hard to earn the bonus
- c. To learn about something interesting
- d. Just for fun, I don't really care how well I did in the task
- e. Other, please specify_____.

Results

In Study 2, the participants were asked to predict the color of a light which shows red or blue randomly, for five 5-trial sets (i.e., 25 trials in total). The choice was coded 1 if the more likely outcome is predicted and 0 otherwise. For each 5-trial sets, we coded the response as 1 if probability-matching strategy was employed and 0 otherwise for the variable MatchingOrNot. Similarly, for the variable MaximizingOrNot, we coded the set 1 if maximizing strategy was used and 0 if not. Thus, the data for each individual consists of five binary variables for matching, and five binary variables for maximizing.

There were three levels of goals we set for different groups of participants to achieve in order to earn certain bonus pay: perfect goal, medium goal, and low goal. Our hypothesis is that there is more probability matching in the perfect goal condition than the low goal and medium goal conditions.

Figure 8 shows the proportion of participants who used a probability matching strategy. It indicates that more participants used the probability matching strategy in the perfect goal (high) condition than in the other two conditions across all five sets. This difference was confirmed by use of a generalized linear mixed model to analyze the binary data for the five sets, with 1 representing a choice of probability matching or maximizing strategy, and 0 representing

not choosing the corresponding strategy. The covariance structures is assumed to be AR(1), assuming that the prediction at time point $t+1$ is correlated to the prediction at time point t .

The main effect of Goal Level (high, medium, or low) was significant, $F(2, 297)=6.25$, $p = .002$. It can be observed from Figure 8 below that in the perfect goal condition, more probability matching strategy was adopted. This result confirms our hypothesis that when perfect prediction of a sequence of outcomes is the explicitly rewarded goal, people are more likely to match predictions in proportion to the probability of the random events. The main effect of Sets was also significant, $F(4, 1188) = 2.88$, $p\text{-value} = .022$, suggesting a non-flat profile overall. However, the Sets x Goal Level interaction was not significant, $F(4, 1188) = .92$, $p = .50$, indicating a generally parallel trend in the three conditions.

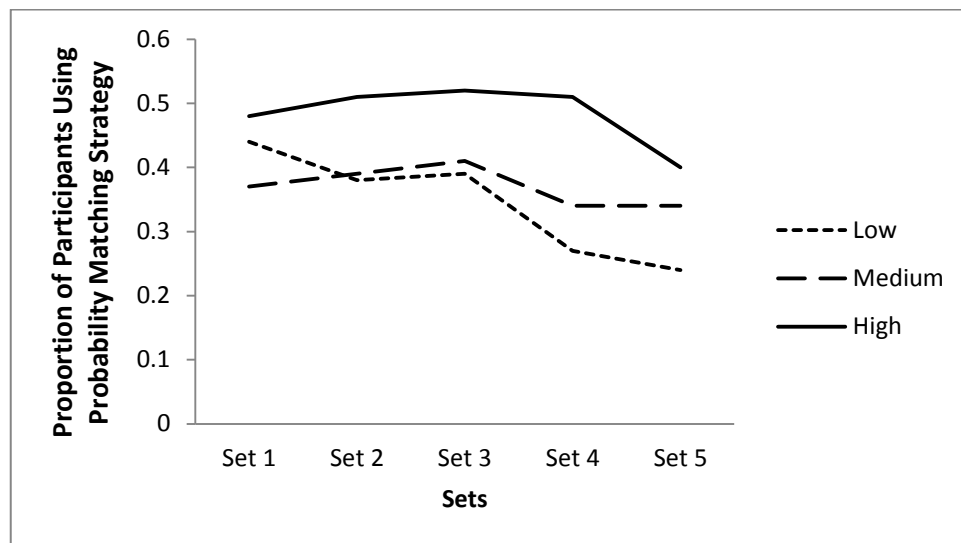


Figure 8 The proportion of participants using a matching strategy across sets in the three goal conditions

The overall mean (and standard error) of the probability-matching indicator variable is shown in Table 6 and Figure 9.

Table 6 Descriptive statistics for the matching variable for different goal-level groups

Goal-level Groups	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Low Goal	.344	.032	.279	.409
Medium Goal	.370	.034	.305	.435
Perfect Goal	.484	.033	.419	.549

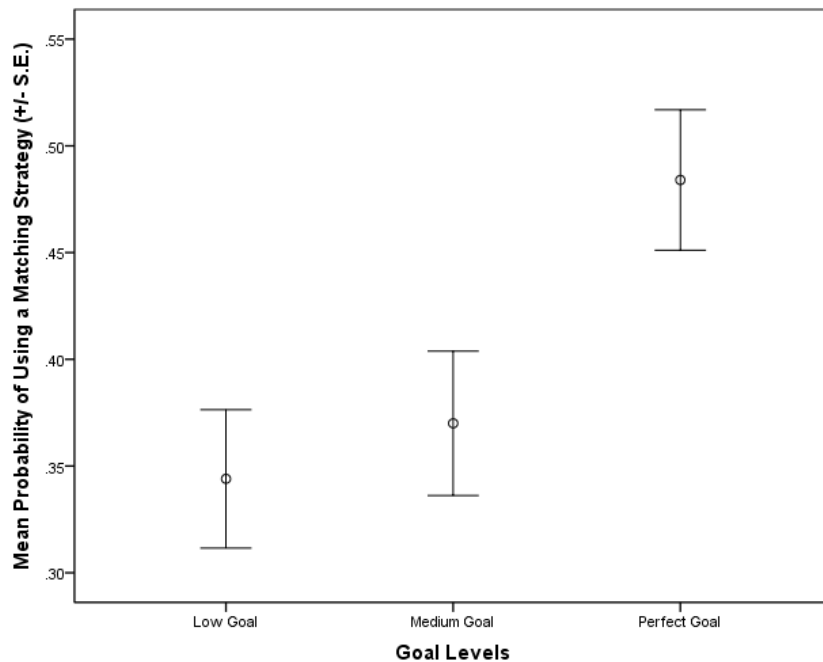


Figure 9 Error-bar plot for mean of matching variables

Figure 10 on the next page shows that the higher prevalence of probability matching in the perfect-goal condition is reflected in a generally lower proportion of maximizing behavior for this condition. The overall proportion of using the maximizing strategy is slightly lower in the perfect goal condition than in the lower goal conditions (0.30, SD=.034 in the perfect goal condition, and 0.32 with SD=.038, .040 in the low goal and medium goal conditions). However, this difference is not significant, $F(2, 297)=.07$, $p = .93$. The main effect of Sets was also

significant, $F(4, 1188) = 5.62$, $p\text{-value} < .001$, which might be due to the apparent increase in use of the maximizing strategy overall as shown in Figure 10. However, the Sets x Goal Level interaction was not significant, $F(8, 1188) = .64$, $p = .75$, indicating a parallel trend between the three conditions.

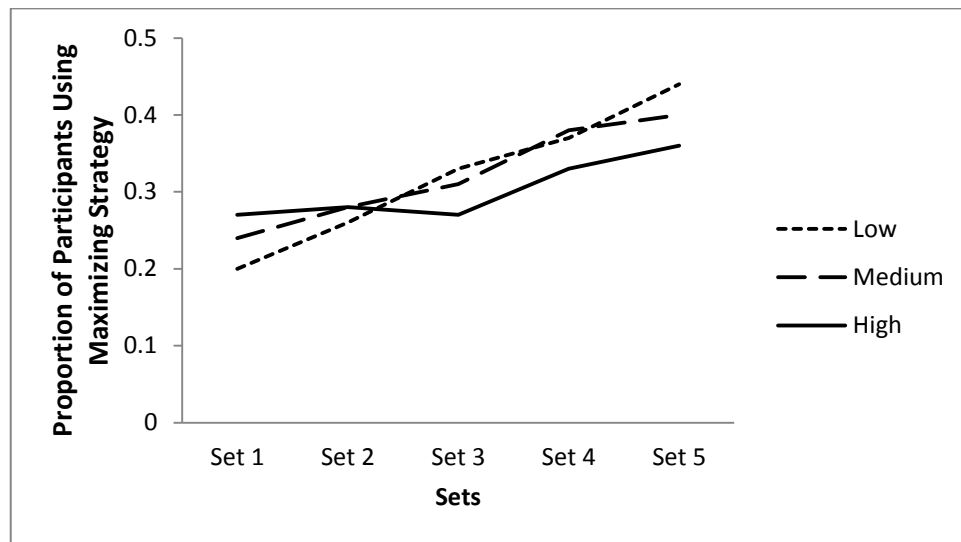


Figure 10 The proportion of participants using maximizing strategy across sets in the three goal conditions

Discussion

Study 2 provides direct evidence that the adoption of a perfect-prediction goal tends to elicit more probability matching behavior in participants. These findings confirm and extend the results of Study 1 because the goal conditions in Study 2 did not differ in how they emphasized sequence-level versus single-trial predictions. Thus, these findings provide more direct support for the hypothesis that adopting a goal of perfect prediction of sequences underlies the phenomenon of probability matching in prediction tasks.

Chapter V STUDY THREE

Introduction

It has been shown that past experience has an important impact on people's reasoning and decision making. For example, pragmatic reasoning schemas theory argues that people reason based on a set of abstract (or partly abstract) knowledge structures induced from daily-life experience (Cheng & Holyoak, 1985). Situating reasoning problems in a real-world context has been found to improve people's reasoning performance in different types of reasoning tasks (Evans, 1982; Johnson-Laird et al., 1972; Wason, 1966; Wason & Evans, 1975). Also, other researchers have reported similar findings indicating a significant impact of previous life experience on perception and cognition, either from their physical world (Tooby & Cosmides, 1992), or from the environment even in domains that are abstracted from or unrelated to the physical environment (cf. Bargh, 2006). Williams, Huang and Bargh (2009) described how higher mental process are grounded in early experience of the physical world, and they named this process *mind scaffolding*. In addition, Fong, Krantz and Nisbett (1986) also argued that during cognitive development, children learned the highly abstract principle of the law of large numbers through experience in many domains. Thus, the effect of related schema on the prediction behavior in the random binary events is a research question of interest in the present study.

The literature on probability matching documents that people often fail to maximize their performance when making sequential predictions. Many of these studies have involved tasks where participants repeatedly predict outcomes for simple randomizing devices: coins or dice. But does this failure to maximize generalize beyond this narrow situation? Would people do

better, or worse, with abstract scenarios, or in story contexts involving 'real-world' situations? We hypothesize that generalization of this failure to maximize may depend on a key aspect of the 'coin-flipping' problem context typically used in studies that find probability matching: the complementary-outcomes nature of the prediction task. In a coin flip, or any type of process with complementary-outcomes, observing that Heads has occurred means that Tails has not. On the other hand, most people have often observed sequences of coin flips, thus they have prior experience observing mixed sequences of outcomes that may impede their ability to find the maximizing strategy if one exists (for a biased coin, that involves predicting pure sequences of the more likely outcome). In particular, we ask if successful maximizing might occur more often if people are choosing between two independent processes rather than between two complementary outcomes.

In binary random events, *independent event* refers to situations where the two outcomes are independent from each other, thus they can both payoff at the same time (or not), each having a certain fixed probability of happening. An (applied) example of independent events would be fishing at two separate locations. Suppose one of the locations pays off 75% of the time, and the other location pays off 25% of the time, respectively. Here people can only choose one of the two locations, and will not be able to know the results that would have been obtained if the other alternative had been selected. This situation is contrasted with *complementary events*, where the two outcomes are mutually exclusive, thus only one of the two outcome events can happen on any single trial. The most obvious example of complementary events is a coin flip, that can result in Heads or Tails. So far, most studies in the research literature about probability matching have used complementary events. An applied example of a complementary event would be if one object were hidden in one of two locations, and it is placed 70% of the time at location A and

30% of the time at location B. In both types of events, the optimal strategy is to choose the more likely outcome for all the trials. However, the behavior in the independent events is expected to be more rational than the complementary events. In independent events, instead of predicting the outcome of one single object for its different stages, people are choosing between two different and independent options. In real life, it is common for people to choose a better option all the time. For example, we choose a better partner to work with for every project we do, etc. We call the mental schema formed from these types of life experience “*pick a winner*”. Therefore, we hypothesize that independent events will lead to more optimal behavior than complementary events do although the payoff probabilities of the two options are the same, because two different schemas are likely to be activated: complementary schema which leads to probability matching and pick-a-winner schema which is more likely to lead to maximizing behavior.

Nisbett et. al (1983) has also found that various cues about a certain reasoning rule in a given problem can dramatically affect the likelihood that people will apply that rule in problem solving. In an extreme case, an arbitrary rule that is not related to ordinary life experiences does not necessarily evoke any reasoning schemas (Cheng & Holyoak, 1985), then people would fail to interpret the arbitrary rule in terms of a reasoning schema, and they would have to turn to formal reasoning. Moreover, Noveck et al. (1991) argued that errors on reasoning tasks do not demonstrate lack of competence, instead, they could result from either “lack of sophistication with reasoning strategies that follow from metalogical analysis”, or from “the application of pragmatic principles to problems that violate pragmatic principles”. This is the reason why Unturbe and Corominas (2007) argued that an abstract task “which is free of contextual cues would be required for assessment of the rule-generating ability”.

Another factor of interest in this study is the abstraction level of the problem contexts. The purpose of having this factor is twofold: firstly, to study whether the schemas' effect can be generalized to different abstraction levels and different problems, if any. Nisbett (1993) mentioned that abstract reasoning rules are not applied to all domains equally, for example, for those who can easily apply statistical rules to random generating devices such as dice, it may be difficult to apply the rules to problems with social content. Secondly, another purpose is to test whether people's prediction behavior differs according to the abstraction level of the problem. It has been found in some tasks that people use only domain-specific rules, and fail to use abstract logic rules to solve concrete problems (e.g., Griggs & Cox, 1982; Manktelow & Evans, 1979). Fong and Nisbett (1991) also mentioned that when the domain of a problem is close to the domain in which people were trained the reasoning rule, it is easier for them to transfer the rule in the new problem. To sum up, we are interested in whether the effect of different event schemas would interact with the abstraction level of problem contexts (as well as any main effect of abstraction level). In the present study, three abstraction levels of context were included: abstract, concrete (random devices), and real-world context.

The experiment is a 2x3 factorial design. The first manipulated factor is the type of schema: whether the outcome events are independent events or complementary events. The second factor is abstraction level of problem context: whether the task is described within an abstract context, a context involving 'concrete' randomizing devices or a socially-situated 'real-world' context. We used a single abstract context (event A vs. B), three concrete-context problems (dice, marbles, spinners), and two real-world problems (basketball players shooting free throws, fisherman catching fish) within each schema condition, for a total of 12 problems in all.

Method

Design

This study is a 2x3 factorial design, with six conditions: independent events under abstract context, independent events under concrete context, independent events under real-world context, complementary events under abstract context, complementary events under concrete context, and complementary events under real-world context. For concrete and real-world context conditions, we ran more than one versions of stories in each condition.

We manipulated the factors by giving different task descriptions to participants in different conditions, as described below. We took care to make sure that the descriptions of the problems were parallel, in order to avoid confounding effects. The instructions given to different groups of participants are shown below.

1. For complementary events conditions under abstract context:

You will be asked to predict 20 trials of a random event. On each trial you will choose one of two options, A or B. Then, either Event A occurs (with probability 2/3) or Event B occurs. If the event you predicted occurs, that trial is a “success”.

2. For complementary events conditions under concrete context:

You will be asked to predict 20 trials of a random event, the color that shows when a single die is rolled. The die has 4 of its faces colored Red, and 2 faces colored White. On each trial you will pick either Red or White, then the die is rolled. If the face of the die that comes up shows the color you picked, that trial is a “success”.

3. For complementary events conditions under concrete context:

You will be asked to predict 20 trials of a random event. First, a single marble is hidden randomly into one of three boxes, labeled A, B, and C. On each trial you have two options: you

can choose Box A, or you can choose Box B AND C. So your choices are “A” or “BC”. If you choose the box(es) with the marble, that trial is a “success”.

4. For complementary events under concrete context:

You will be asked to predict the results of 20 trials, where each trial is a spin of a spinner. The spinner is divided into three equal areas, two of them colored red and one colored white. On each trial, you will first pick one of the two colors, then the pointer will be spun. If the pointer lands on the color you picked, that trial is a “success”.

5. For complementary events under real-world context:

You will be asked to predict hits and misses as a basketball player; Player X, shoots 20 free throws. Player X hits $\frac{2}{3}$ of his free throws on average. On each trial you will predict Hit or Miss. If you predict correctly, that trial is a “success.”

6. For complementary events under real-world context:

You will be asked to predict successful outcomes for a fisherman across 20 days of fishing. In the stream where the fisherman is fishing, $\frac{2}{3}$ of the trout are Rainbow trout and $\frac{1}{3}$ of the trout are Brook trout. Your task is to predict whether each fish caught will be a Rainbow trout or a Brook trout. For every fish caught, if the fisherman catches a trout that matches your prediction (Rainbow or Brook), that trial is a “success.”

7. For independent events conditions under abstract context:

You will be asked to predict 20 trials of a random event. On each trial, you will choose one of two options, A or B. On any trial, Option A has a $\frac{2}{3}$ chance of showing a “success”. Independently, on any trial Option B has a $\frac{1}{3}$ chance of showing a “success”. Your goal is to choose one that shows a “success”.

8. For independent events condition under concrete context:

You will be asked to predict 20 trials of a random event, whether a die with colored faces shows a Red face when it is rolled. There are two dice, Die A and Die B. Die A has 4 of its faces colored Red, and 2 faces colored White. Die B has 2 of its faces colored Red, and 4 faces colored White. On each trial you will pick one of the two dice. If the face of the die you picked shows Red, that trial is a “success”.

9. For independent events condition under concrete context:

You will be asked to predict 20 trials of a random event, the selection of a Red marble. On each trial, you will choose one of two boxes, Box A or Box B. Box A contains 20 Red marbles and 10 White marbles. Box B contains 10 Red marbles and 20 White marbles. After you pick a box, one marble will be randomly selected from the box you selected. If the marble drawn is Red, that trial is a “success”.

10. For independent events conditions under concrete context:

You will be asked to predict the results of 20 trials, where each trial is a spin of a spinner. There are two spinners, A and B. Spinner A is divided into three equal areas, two of them colored red and one colored white. Spinner B has three equal areas, one red and two white. After you pick a spinner, the pointers of both spinners will be spun. If the pointer of the spinner you picked lands on the color Red, that trial is a “success”.

11. For independent events under real-world context:

You are participating in a basketball free-throw shooting contest. Your team consists of two players, A and B. Player A hits $\frac{2}{3}$ of his free throws on average, while Player B hits $\frac{1}{3}$ of his free throws on average. On each trial, you get to select a player to take a single free throw. If the player you select hits that free throw, that trial is a “success”.

12. For independent events under real-world context:

You will be asked to predict successful outcomes for fishermen across 20 days of fishing. On each day, you can select a fisherman fishing in West Pond, where 2/3 of the time people successfully catch at least one fish, or you can select a fisherman fishing in East Pond, where 1/3 of the time people successfully catch at least one fish. At the end of each day, if the fisherman you selected has caught at least one fish, that trial is a 'success'."

After the prediction tasks, a questionnaire asking about participants' strategy and their demographic information was given. They were also asked about their main reason for participating in our experiment.

Participants

As in Studies 1 and 2, participants were recruited from Amazon's Mechanical Turk, where registered users selected the tasks that they wanted to participate in. In this study, they were randomly assigned to one of the 12 conditions upon entering the experiment. We specified in our instruction that each participants can only do this task for once, and subsequent tasks would not be accepted. All workers who have participated in the previous studies were blocked, so that we can prevent duplicate workers in the future conditions of the tasks, therefore all participants in Study 1 and Study 2 did not have access to this study. The task took about 5 minutes to complete.

The participants were randomly directed to one of the conditions of this study, and were evenly distributed among conditions. We recruited 25 participants for each condition, so the total sample size is 300. In this sample, the average age is 29.31, ranging from 13 to 68. Gender was 38.7% female and 61% male, with 0.3% not specified.

Participants were paid \$0.25 as the base pay for completing the study, plus a performance-based bonus payment (in the amount of \$0.05 for each of the trials that they predict correctly).

Procedure

In this experiment volunteer participants were randomly directed to one of the 12 conditions. They first read the instructions according to the conditions they were assigned to, as described earlier. In the instructions, they were told the background story, representing different types of events under either abstract, concrete or real-world contexts, and also the probabilities of each outcome event.

After reading the instructions, participants were asked to complete a choice/prediction task of a series of random binary events, by clicking one of the two buttons on the screen. For complementary events task such as the tasks in Study 1 or Study 2, the participants were predicting which of the two outcomes of one random event would take place in the next trial. For independent events task, they were choosing from two random events, where the two alternatives were independent from each other, as shown in the instructions given in the previous Method Design section.

In each of the four conditions, they had 20 chances to predict the outcomes or choose their preferred alternatives. Each time after they made a decision, they were shown the actual outcome. They were also notified in words whether their prediction or choice was a “success” (i.e., paid off) in the current trial, as well as the amount of bonus they had win. After the prediction/choice trials, all participants were required to complete a questionnaire about the

strategies they used. The form also asked for their basic demographic information, such as gender, age, math ability and education background.

Results

As described above, two proposed factors were investigated in this study: type of event schema, and the abstraction levels of the event context. The two types of event schema studied were *complementary events* and *independent events*; and there were three types of abstraction level of contexts: *abstract context*, *concrete random device context*, and *real-world context*. To increase the generalizability of the study, multiple stories were used in concrete and real-world contexts, as shown in Table 7.

The probability of choosing the more likely event (the “rational” option) was compared across conditions. The prediction was coded 1 if the rational choice is made (meaning to choose the outcome with higher probability of paying off), and 0 other wise. The mean probability of choosing the more likely outcome is shown in Table 8 on the next page, and a significance tests is shown afterwards.

Table 7 Conditions and stories in Study 3

	Independent	Complementary
Abstract	1 condition	1 condition
Concrete	Die, Marble, Spinner	Die, Marble, Spinner
Real-world	Basketball, fishing	Basketball, fishing

Table 8 Descriptive Statistics for Each Condition

Schema Type	StoryPair	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Complementary	Abstract (A or B)	.748	.0513	.674	.822
	Die(s)	.830	.0368	.756	.904
	Marble(s)	.830	.0375	.756	.904
	Spinner(s)	.706	.0438	.632	.780
	Basketball Player(s)	.792	.0293	.718	.866
	Fishing	.760	.0333	.686	.834
Independent	Abstract (A or B)	.834	.0384	.760	.908
	Die(s)	.862	.0350	.788	.936
	Marble(s)	.816	.0324	.742	.890
	Spinner(s)	.796	.0423	.722	.870
	Basketball Player(s)	.834	.0361	.760	.908
	Fishing	.868	.0312	.794	.942

Effect of Schema Type

The descriptive statistics showed that for complementary events, less maximizing behavior was observed (Mean = .778, SD = .016) than with independent events (Mean proportion = .835, SD = .014).

Figure 11 on the next page shows the probability of choosing the more likely outcome across four “pseudo sets”, each with five trials. Although the division of sets is arbitrary, it is useful for graphing purposes, to show that maximizing behavior is consistently more prevalent in the independent events than in the complementary events, across the whole task.

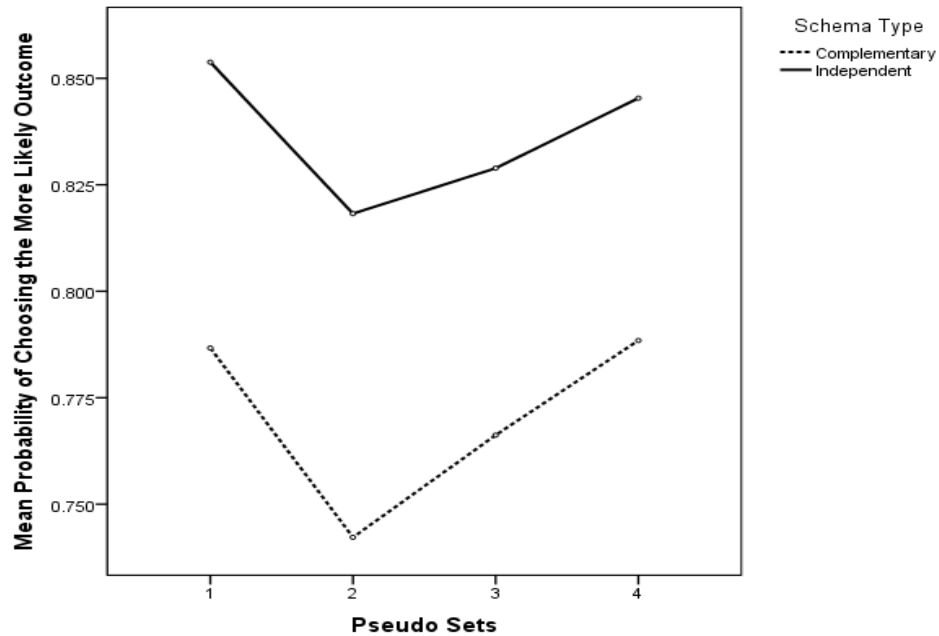


Figure 11 Profile plot of the probability of choosing the more likely outcome (Schema Type x Sets)

The 20 binary variables indicating the choice of each trial were analyzed using a generalized linear mixed model (GLMM). The covariance structures is assumed to be AR(1), assuming that the prediction at time point $t+1$ is correlated to the prediction at time point t . The results show that the main effect of schema type is significant, $F(1, 5918) = 20.418$ $p < .001$. This result is consistent with our expectation that independent events will lead to more maximizing behavior because of the “pick a winner” schema which makes it more reasonable to predict the more likely outcome for all the trials.

The main effect of schema type can be generalized among different abstraction levels of contexts as shown in Figure 15: there was no significant interaction effect with abstraction level of context (abstract, concrete, real-world), $F(2, 5918) = 1.396$ $p = .248$, and independent events led to more choice of the optimal strategy for all three context levels as suggested by Figure 12 on the next page.

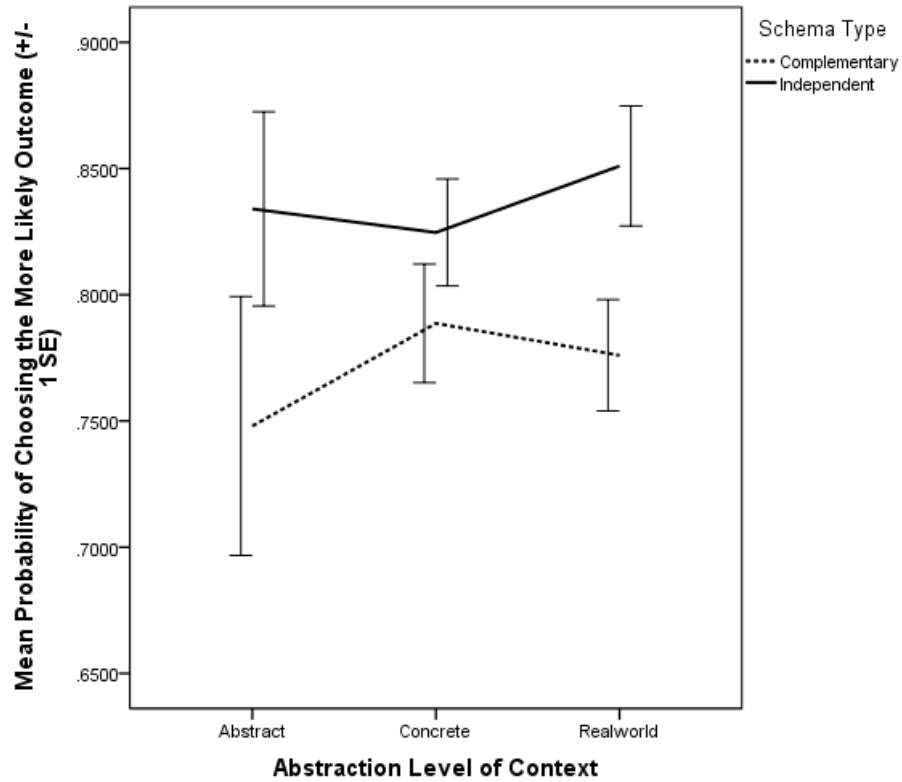


Figure 12 Profile plot of the probability of choosing the more likely outcome (Schema Type x Context Level)

Effect of Context

The descriptive statistics for the mean probability of choosing the more likely outcome: for the abstract context (Mean proportion = .791, SD = .027), concrete context (Mean proportion = .807, SD = .015), and the real-world context (Mean proportion = .813, SD = .019).

Figure 13 shows the probability of choosing the more likely outcome across four pseudo sets, each with five trials.

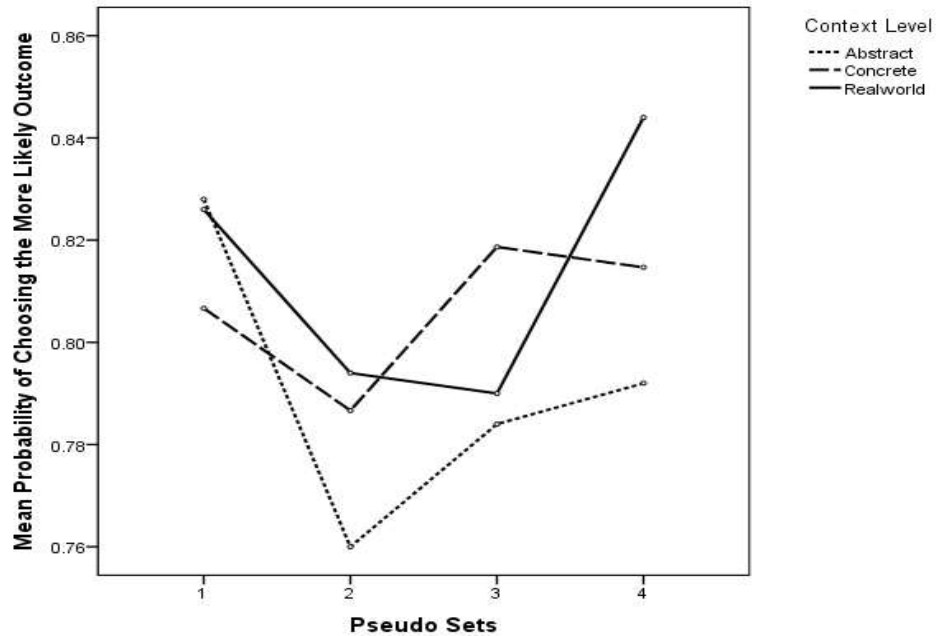


Figure 13 Profile plot of the probability of choosing the more likely outcome, under the different contexts

The 20 binary variables indicating the choice of each trial was analyzed using the same generalized linear mixed model (GLMM), and the results show that the main effect of context is not significant, $F(2, 5918) = .475$, $p = .62$. This result shows that the probability of choosing the more likely outcome is not affected by the context level of a task, whether it is abstract, or concrete random devices, or real-world stories.

Discussion

The results support our hypothesis that problems exemplifying the complementary-outcomes schema may make it especially difficult for people to discover the maximizing strategy, while when people are primed to choose between two objects (a common instantiation of the independent events schema), it would be easier to maximize due to the “pick a winner”

pragmatic schema. The results shed light on cognitive factors that affect why, and when, people are successful in finding maximizing strategies. We suspect that people's difficulty in finding the maximizing strategy for complementary events may be due to prior experience (and related to a representativeness heuristic) -- it is natural to envision mixed sequences for a coin flip, but less natural to envision a sequence of all Heads (for example) for the same object. Yet such pure sequences correspond to the optimal maximizing choice strategy. However, when two distinct "objects" are involved (as is often true for independent events), it is more natural to 'pick a winner' and stick with that person or location that yields the best individual trial-level outcome as in real life, leading to optimal pure sequences of choices (or optimal pure sequences of successes).

Differences in the proportion of rational prediction behavior between these two schema types were consistently observed across the three different abstraction levels of event contexts, and no significant interactions were found. Thus, the main effect of complementary- versus independent-events schema generalized to different abstraction levels of context: in abstract, concrete or real-world context. We included more than one random device and more than one real-world stories, and the effect was observed in all contexts. Thus, it seems reasonable to conclude that the type of schema: complementary versus independent events, has a strong and consistent effect on prediction behavior in random binary events.

However, in contrast to what pragmatic schema would predict, the main effect of abstraction levels of context was not found to have a significant effect on people's rational choice. Pragmatic schema effects have been found to help people to apply abstract reasoning rules to problem solving (e.g., Wason, 1966). However, in our study, the task might have

involved more intuition-based decision processes, instead of formal reasoning. This might explain why no significant differences between abstraction levels were observed.

An alternative to the schema-based account might be to argue that the complementary events and independent events offer different types of information about foregone payoffs (Yechiam & Busemeyer 2006): the occurrence of one event in a pair of complementary events (such as Heads) provides certainty that the complementary event (Tails) did not occur, whereas for a fishing location catching a fish in one location provides no information about whether one would have experienced a payoff by selecting the other location. However, this factor should not affect our conclusion in this study. In previous research, forgone payoff information was found to be helpful for people's learning of probability in random binary prediction tasks when the payoff probabilities were unknown to the participants. In our study, there is no probability learning task involved. Even if we assume it does, it should not affect our finding: it was the independent events that missed offering this information, thus, if forgone payoff information was offered in order to parallel the complementary events, it would increase the level of rational choice in this condition, indicating an even more significant effect.

In previous chapters, we have proposed the adoption of implicit perfect prediction goals as a factor affecting probability matching behavior. That factor might also be playing a role in this study. For complementary events, it is "either A or B", thus there is always a "correct" answer and a "wrong" answer; while for independent event, it is "better A or better B", thus it is obvious that neither of the two options can lead to a perfect result. Therefore, the independent events might force people to abandon the perfect prediction goal, and hence lead to more rational choices. However, this potential explanation would need to be verified in future studies.

We found no effect of using concrete or real-world contexts on tendency to maximize in Study 3. This null result does not prove that story context is unimportant. Although we chose more than one background story, there might be large variability in the benefit of different "real-world" topics or narratives. For example, Cosmides' (1989) results suggested that in the Wason Selection Task, concreteness of the stories in itself is no help; familiarity is somewhat helpful; but social contract narratives, even when their content is unfamiliar, are of big help. Thus, in our Study 3, if the stories involved known social contract situations such as cheater detection, there might be more maximizing in both independent and complementary-event schemas. Future experiments are needed in order to investigate this idea.

Chapter VI GENERAL DISCUSSION

The results of Study 1, showing that emphasizing and rewarding perfect prediction of sequences leads to more use of the “irrational” probability matching strategy, are consistent with recent findings by James & Koehler (2011). In two experiments, they found that having participants make predictions for 10 unique games, all with equivalent outcome probabilities, led to less matching and more maximization than making predictions for 10 repeated trials of a single game. They interpreted the results in that “this is because the individuating features made it less likely that participants would generate and apply sequence-wide expectations to the binary prediction task”. In a third experiment, in one condition (“global focus”) they encouraged generation of sequence-level expectations by asking participants “In 10 rolls of the die, how many times would you expect each outcome?” before the prediction task. In a contrasting “local focus” condition, they asked: “On any individual roll of the die, which color is more likely to be rolled?” The local-focus condition led to more maximizing and less matching. One caveat that James and Koehler mention is that no actual rewards were offered for performance in their experiment. The results of our Study 1, that emphasizing and *explicitly rewarding* sequence-level predictions lead to increased probability matching, thus complement and extend James and Koehler’s results.

Our results (and those of James and Koehler) cannot be explained away in terms of task difficulty. It might be argued that predicting the results of a sequence is somehow more difficult than predicting a series of individual outcomes, thus explaining a lower rate of maximizing. But this seems unconvincing when the participant’s task is merely to generate a string of predicted

outcomes. Furthermore, the “global-focus” manipulation of James and Koehler’s Experiment 3 not only asked participants to think about a sequence, but explicitly asked them to generate an expectation for the sequence in terms of *frequencies* of the two outcomes. Gigerenzer and Hoffrage (1995) have argued that many documented “irrationalities” in human probabilistic reasoning can be ameliorated by posing judgment problems in terms of frequencies rather than probabilities (which were emphasized in James and Koehler’s “local focus” condition). Thus it is somewhat counterintuitive that the global-focus manipulation led to lower matching. This lends support to the idea that prediction of sequences is special in some way.

Our Study 2 results suggest that *performance goals* may play an important role in linking sequence-level beliefs and expectations to behavior. We emphasize that a goal-based account of probability matching is not inconsistent with expectation-matching explanations. Rather, the idea that implicit (or explicit) adoption of a perfect-prediction goal increases matching behavior may help to elaborate the expectation-matching viewpoint, highlighting one mechanism by which sequence-level expectations can lead to probability matching behavior. More generally, the present results lend support to the argument that goals play a critical role in human decision-making (Krantz & Kunreuther, 2007).

We have invoked the idea of representativeness to explain why participants attempt to achieve a perfect prediction goal by probability matching, i.e. by generating strings of predictions with outcome probabilities matching the specified (or observed) distribution of outcomes. This idea, and the argument that such a response strategy is a form of “attribute substitution” (James & Koehler, 2011; Morewedge & Kahneman, 2010), suggest that the phenomenon of probability matching is not an anomaly, but rather arises from general cognitive heuristics and biases. In fact, another well-documented bias in judgment besides

representativeness, namely the conjunction fallacy (Tversky & Kahneman, 1983), may also play a role, by misleading participants into the apparent belief that it can be a realistic goal to perfectly predict a sequence of outcomes. The conjunction fallacy describes the naïve tendency to overestimate the probability of joint outcomes involving multiple events (here, prediction of all outcomes in a sequence). This fallacy may be one reason why a perfect prediction goal seems plausible and attainable to participants in repeated prediction tasks.

In addition, our results also show that experience with the prediction task (and appropriate feedback) leads to improving performance, as demonstrated by the group data showing an increase in use of the optimal maximizing strategy across sets of trials. This finding is consistent with previous empirical investigations (e.g., Shanks, Tunney, & McCarthy, 2002; Vulkan, 2000; West & Stanovich, 2003). In our tasks the probabilities of the two possible outcomes were provided to participants at the outset, therefore this improvement cannot be ascribed to probability learning. Rather it must be due to some form of strategy learning, or perhaps to a shift in goals. Further research into how people formulate and apply strategies, and improve or abandon them when they prove unsatisfactory in achieving current goals, may be warranted.

Study 3 investigates additional factors that might be affecting the choice of a maximizing strategy. The main factor we proposed was the type of underlying schema for the problem: complementary events or independent events. It was found in our Study 3 that when the complementary schema was more active (i.e., for complementary events), people were less likely to use the maximizing strategy and make the optimal choice. In independent events, where the schema we call “pick a winner” fits better, more optimal choices were observed. This effect was consistently observed in different background stories, with different levels of abstraction.

However, contrary to the predictions of pragmatic schema theory, the main effect of context was not found to be significant in our study. Previous research has shown that pragmatic schema, triggered by certain real-world problem contexts, are able to help people to apply abstract reasoning rules to problem solving. In our study, the task can be performed with more intuition-based process, instead of formal reasoning. This may be why no significant difference was observed with concrete contexts. Alternatively, it may be that the real-world contexts we implemented may not have been familiar enough to participants to invoke pragmatic schema learned through experience.

A possible generalizability issue with the present findings is that all three studies were conducted on Amazon's Mechanical Turk (MTurk). MTurk is a crowdsourcing platform, which enables task creation, labor recruitment, compensation and data collection. Using this source of participants may affect the results, compared to other participant sources such as college students and regular Internet recruitment. However, diversity has been found to be quite high in MTurk samples. Pontin (2007) reported that there are over 100,000 users from over 100 countries who complete tens of thousands of tasks daily on the MTurk. Buhrmester, Kwang and Gosling (2011) investigated the possible effects of collecting data from the Mturk, and found that: 1) The diversity on MTurk is higher than standard Internet samples, based on a sample of 3006 participants; 2) The participation rate is effected by the compensation amount (positive effect) and task length (negative effect); 3) Participants are "not driven primarily by financial incentives", but by other internal motivation such as enjoyment; 4) The low compensation rate only affects the speed of data collection, not the data quality, based on the alpha reliability index; 5) The data from MTurk meets high standard psychometric standard: high alpha reliability index

(mean of .87), high test-retest reliability ($r = .88$). Thus, if these results apply to our studies, then we do not need to worry about the data quality nor the participants' demographical diversity.

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Appendix A. Study 1

1. Probability of choosing the more likely outcome

In order to graph the results, we divided the 100 trials into 10 blocks, and the probability of choosing the more likely option in each block was calculated and graphed; for the no-bias conditions, the probability of choosing the Red light in each block is shown.

Figure 14 shows the resulting response curves of the likelihood of guessing the more likely outcome for bias conditions, and the color Red for no-bias conditions. As is apparent from the graph, *probability bias* had the greatest effect on responses. In the no-bias (50-50%) condition, participants emitted a roughly equiprobable mix of guesses across the 100 trials, consistent with probability matching. In the bias (75%-25%) condition, participants start out emitting just under 75% predictions of the more-likely outcome, reflecting predominantly matching behavior, with some bias towards an equiprobable distribution. But with experience, probability maximizing becomes more prevalent, causing the overall curve to drift upwards to a final value of approximately 85% (apparently reflecting a mix of matching and maximizing, across subjects). Differences were observed between the single-trial and pattern conditions, in that the response curves for the pattern condition were consistently closer to the 75% level diagnostic of pattern-matching across all blocks. However, in the no-bias conditions, the probability of choosing the Red light is around 50% across all blocks, for both single-trial and pattern conditions.

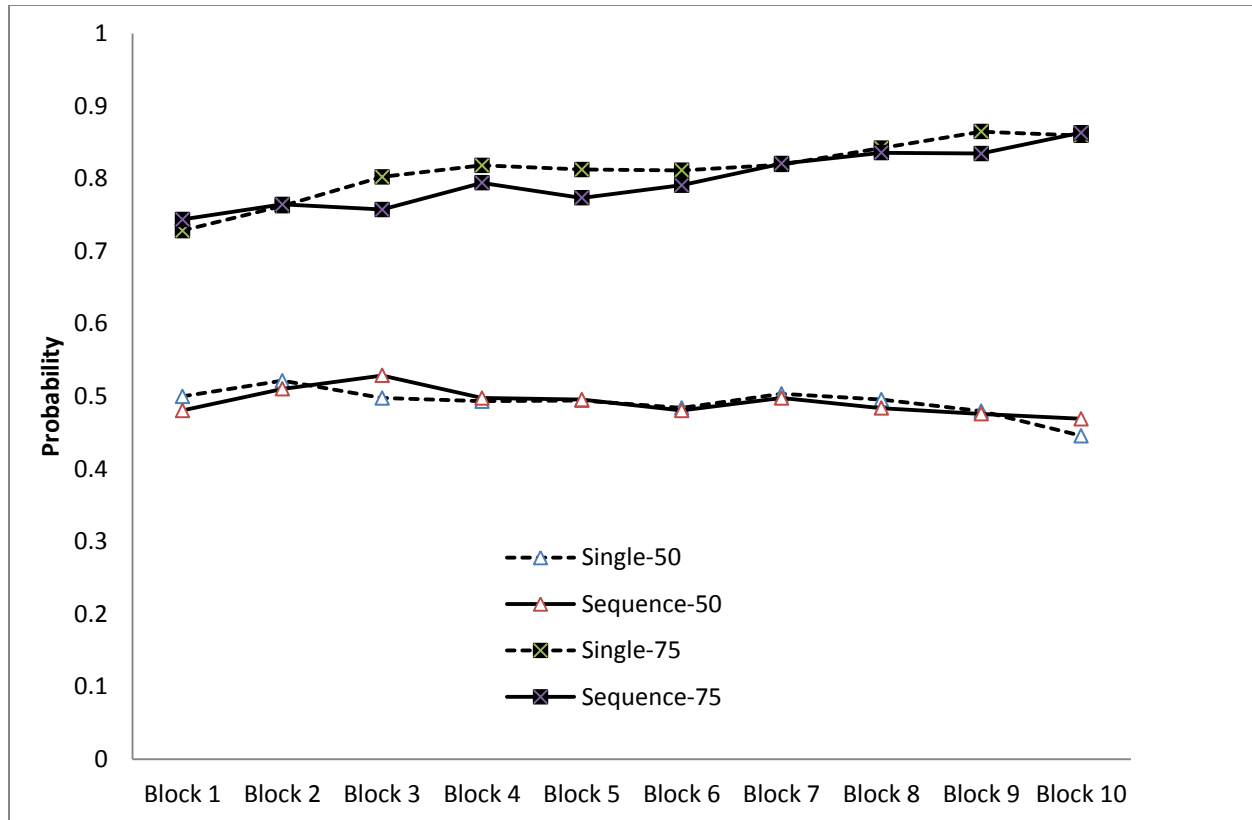


Figure 14 The probability of predicting the more likely outcome for bias conditions, and the probability of choosing Red light for no-bias conditions

2. Earned Payoff information

Table 9 below shows the actual earned bonus (mean and standard deviation), and expected bonus for a pure matching strategy and a pure maximizing strategy (in dollars).

In order to calculate the expected bonus, the first step is to calculate the expected scores. For the single-trial no-bias conditions, the expected score for a pure matching strategy is $.5 \times 100 = 50$. Since the bonus for each single correctly predicted trial was \$.01, the total expected bonus is $50 \times \$0.01 = \0.50 . The expected bonus is the same for a pure maximizing strategy (choosing one color consistently). For the sequence no-bias conditions, the expected number of correctly predicted *sequences* for a pure matching strategy is $(.5)^4 \times 25 = 1.56$. Since the bonus per

sequence is \$0.10, the total expected bonus should be $1.56 * \$0.10 = \0.156 . The expected bonus is the same for a pure maximizing strategy (choosing one color consistently).

For the single-trial bias conditions, the expected score for a pure matching strategy is $(10/16) * 100 = 62.5$. Since the bonus for each single correctly predicted trial was \$0.01, the total expected bonus is $62.5 * \$0.01 = \0.625 . For a pure maximizing strategy, the expected score is 75, thus the expected bonus pay is $75 * \$0.01 = \0.75 . For the sequence no-bias conditions, the expected number of correctly predicted sequences for a pure matching strategy is $(10/16)^4 * 25 = 3.81$. Since the bonus for each single correctly predicted sequence was \$0.10, the total expected bonus is $3.81 * \$0.10 = \0.381 . For a pure maximizing strategy, the expected score is $(3/4)^4 * 25 = 7.91$, thus the expected bonus pay is $7.91 * \$0.10 = \0.791 .

Table 9. Bonus Information for Study 1 (Earned and Expected)

Condition	Earned Bonus (Mean, Std. Deviation)	Expected Bonus (Pure Matching)	Expected Bonus (Pure Maximizing)
Single 50	.494 (.052)	.500	
Sequence 50	.148 (.126)	.156	
Single 75	.660 (.063)	.625	.750
Sequence 75	.421 (.236)	.381	.791

3. ANOVA Tables

The following tables (Table 10, Table 11, and Table 12) are the ANOVA table output for the Study 1 data using the GLIMMIX procedure in SAS.

Table 10. ANOVA Table for No-Bias Condition (DV=Matching)

Effect	df1	df2	F-Value	Pr > F
SingleOrPattern	1	173	74.62	<.0001
Sets	24	4152	1.35	0.118

Table 11. ANOVA Table for Bias Condition (DV=Matching)

Effect	df1	df2	F-Value	Pr > F
SingleOrPattern	1	173	37.89	<.0001
Sets	24	4152	1.71	0.017

SingleOrPattern*Sets	24	4152	1.64	0.025
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Table 12. ANOVA Table for Bias Condition (DV=Maximizing)

Effect	df1	df2	F-Value	Pr > F
SingleOrPattern	1	173	14.26	0.0002
Sets	24	4152	3.28	<.0001
SingleOrPattern*Sets	24	4152	1.37	0.107

4. Analysis of Individual Differences

In Chapter III, the behaviors in the first five sets and last five sets were shown in the histograms in Figure 6 and Figure 7. However, this information only reflects the group level distribution of behaviors, not the individual level. In order to investigate the individual differences in terms of their strategy's change, the first five sets and the last five sets were selected to represent people's initial and ending behaviors.

The participants were defined as Matchers if matching behavior was observed for three or more sets in the five sets. The participants were defined as Maximizers if maximizing behavior was observed for three or more sets in the five sets.

Then we divided the participants into four categories as described below, and the frequencies are shown in Table 13 and Table 14.

- 1) *Consistent Matcher/Maximizer*: defined as matchers/maximizer in both first and last five sets.
- 2) *Giving-up Matcher/Maximizer*: defined as matchers/ maximizers in the first five sets, but not in the last five sets.
- 3) *New Matcher/Maximizer*: defined as not matchers/ maximizers in the first five sets but were matchers/ maximizers in the last five sets.

- 4) *Consistent Non-matcher/Non-maximizer*: defined as not matchers/ maximizers in both first and last five sets.

Table 13. Individual Differences: Frequencies of Participants Showing Various Patterns of Matching Behavior

Condition	Consistent Matcher	Giving-up Matcher	New Matcher	Consistent Non-matcher	Total
Single 50	5	16	14	53	88
Sequence 50	24	21	18	24	87
Single 75	1	16	13	58	88
Sequence 75	15	30	8	34	87
Total	45	83	53	169	350

Table 14. Individual Differences: Frequencies of Participants Showing Various Patterns of Maximizing Behavior

Condition	Consistent Maximizer	Giving-up Maximizer	New Maximizer	Consistent Non-Maximizer	Total
Single 50	8	4	6	18	36
Sequence 50	3	3	6	75	87
Single 75	23	6	35	24	88
Sequence 75	21	2	27	37	87
Total	55	15	74	206	350

The tables above show that for the bias conditions, 1) there were more people who gave up the matching strategy than those who started to use the matching strategy in the end; 2) giving-up maximizers were very few comparing to the other categories, indicating that few people abandoned a maximizing strategy after using it. In contrast, many people began to use it in the last five sets (New Maximizers).

Appendix B. Study 2

1. Probability of choosing the more likely outcome

Figure 15 shows the probability of choosing the more likely event in the 5-trial sets in Study 2. It shows that people chose the more likely event more often in the perfect goal condition than those in the other conditions. Also, we observed more rational choice towards the end of the experiment in all three conditions. The use of probability matching strategy is analyzed and graphed later.

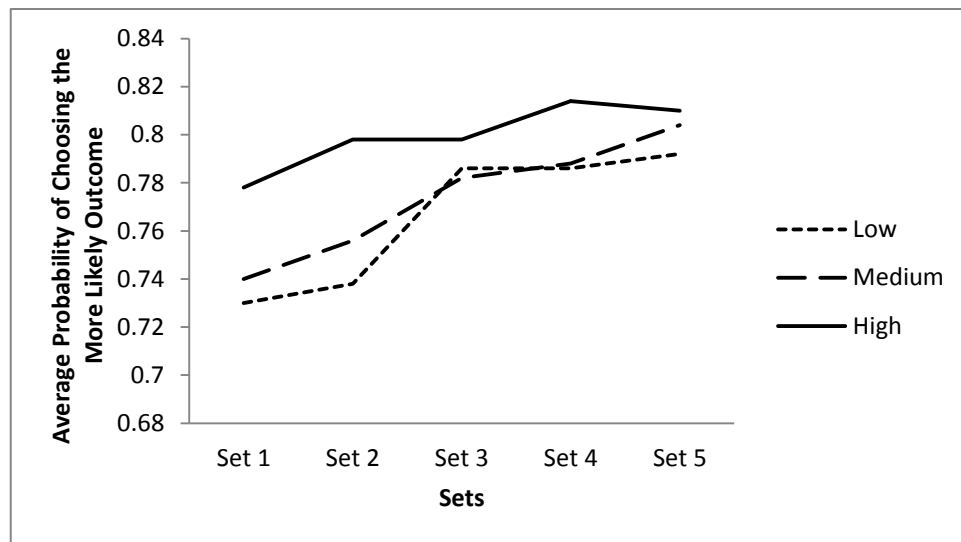


Figure 15 The probability of choosing the more likely event across the 5-trial sets in the three goal conditions

2. Earned Payoff information

The expected probability of earning a bonus in each sequence was simulated, and the results are listed in the following Table 15. Table 16 shows the earned total bonus (mean and standard deviation), and expected total bonus for pure matching strategy and pure maximizing strategy (in dollars).

Table 15 Expected Score Calculation Results

Condition	Expected probability of predicting one sequence correctly		Expected number of correctly predicted sequences	
	Matching	Maximizing	Matching	Maximizing
Low Goal	.85	.94	4.250	4.70
Medium Goal	.49	.74	2.450	3.70
High Goal	.081	.33	0.405	1.65

Table 16. Payoff Information for Study 2 (Earned and Expected Bonus)

Condition	Earned Bonus (Mean, Std. deviation)	Expected Bonus (Matching)	Expected Bonus (Maximizing)
Low Goal	\$0.483, (.131)	\$0.638	\$0.705
Medium Goal	\$0.290, (.187)	\$0.368	\$0.555
High Goal	\$0.086, (.119)	\$0.061	\$0.248

Score:

3. ANOVA Tables

The following tables (Table 17 and Table 18) are the ANOVA table output for the Study 2 data using the GLIMMIX procedure in SAS.

Table 17. ANOVA Table for Matching

Effect	df1	df2	F-Value	Pr > F
GoalLevel	2	297	6.25	0.0022
Sets	4	1188	2.88	0.0216
GoalLevel*Sets	8	1188	0.92	0.496

Table 18. ANOVA Table for Maximizing

Effect	df1	df2	F-Value	Pr > F
GoalLevel	2	297	0.07	0.931
Sets	4	1188	5.62	0.0002
GoalLevel*Sets	8	1188	0.64	0.7462

4. Survey Analysis

The questionnaire included five questions in addition to demographic questions. The results were coded and are shown in the following tables.

1) "What strategy did you use to make your predictions?"

The verbal responses were coded as indicating self-reported Matching, Maximizing, Random(or Stochastic), and Unclear. The distributions of the four types of strategies across the three levels of goals are shown in Table 19. The distribution is basically similar across conditions, however, there is less maximization is reported in the high goal condition than in the other two goal levels.

Table 19. Distribution of Coded Responses to Survey Question 1 in Study 2

	Low Goal	Medium Goal	High Goal	Total
Matching	37	32	35	104
Maximizing	30	31	22	83
Random/Stochastic	21	25	29	75
Unclear	12	12	14	38
Total	100	100	100	300

2) “Did you change your strategy?”

Table 20 below shows the distribution of people’s responses to this question. For all three goal levels, the majority of people claimed that they did not change their strategies during the prediction task.

Table 20. Distribution of Responses to Survey Question 2a in Study 2

	Low Goal	Medium Goal	High Goal	Total
Yes	33	48	38	119
No	66	52	62	180
Blank	1	0	0	1
Total	100	100	100	300

“If yes, why did you change it?”

For all three goal levels, among those who reported to have changed their strategies during the prediction task, we coded their description of how they changed their strategies in to Certain Rule (e.g., “The last one in each set is always blue”), Guess (random guessing),

Matching (e.g., “I make sure there is one Blue in each set, and four Red”), Maximizing, and Unclear.

Table 21 below shows the distribution of people’s responses to this question: there were about 25% people changed their strategy according to certain rule they decided to follow, or pattern they claimed to have found. Few people changed their strategies from other strategy to matching. More maximizing was observed, meaning most of them changed to maximizing strategy.

Table 21. Distribution of Responses to Survey Question 2b in Study 2

	Low Goal	Low Goal Proportion	Medium Goal	Medium Goal Proportion	High Goal	High Goal Proportion	Total	Total Proportion
Certain Rule	8	0.24	11	0.23	12	.32	31	0.26
Guess	1	0.03	4	.08	4	.11	9	0.08
Match	4	0.12	5	.10	3	.08	12	0.10
Max	20	0.61	23	.48	16	.42	59	0.50
Unclear	0	0.00	5	.10	3	.08	8	0.07
Total	33	1.00	48	1.00	38	1.00	119	1.00

3) “If you did the prediction task again, would you change your prediction strategy?”

“If yes, in what way?”

Table 22 on the next page shows the distribution of people’s responses to this question. In all three goal levels, the majority of people claimed that they would not change their strategies in a future prediction task.

Among those who would change their strategies in a future prediction task, we coded their description of how they would change their strategies in to Random (random guessing), Matching (e.g., “I make sure there is one Blue in each set, and four Red”), Maximizing, and Unclear. Few people would change their strategies from other strategy to matching. Most of them would change to maximizing strategy. In the high goal condition, there were relatively more

people would change to a matching strategy in the future, and less people would change to a maximizing strategy in the future, comparing to the low goal and medium goal conditions.

Table 22. Distribution (Frequencies) of Responses to Survey Question 3 in Study 2

		Low	Medium	High	
Type of Response		Goal	Goal	Goal	Total
Not Change		84	62	70	216
Change	Match	1	7	9	17
	Max	12	24	12	48
	Random	2	3	4	9
	Unclear	1	4	5	10
Total		100	100	100	300

4) “How likely it is for you to win the bonus if you do this task again?”

Table 23 below shows the distribution of people’s responses to this question, as well as the expected probability of earning the payoff in one set. In the low goal condition, the estimated probability was lower than expected probability using either matching or maximizing strategy; in the medium goal condition, the estimated probability was between the two; while in the high goal condition, the estimated probability was higher than both, indicating a trend of overoptimistic.

Table 23. Distribution of Responses (Mean estimated probability of winning) to Survey Question 4 in Study 2

Condition	Mean	Std. Deviation	Expected Probability (Maximizing)	Expected Probability (Matching)
Low Goal	.72	.25	.94	.85
Medium Goal	.63	.31	.74	.49
High Goal	.39	.31	.33	.08

5) “What are you participating this study for (please check all that apply)?”

Table 24. Distribution of Responses to Survey Question 5 in Study 2

Options	Frequency	Percentage
A For the payment, especially the bonus	204	68%
B For the base pay, I didn’t try hard to earn the bonus	58	19.3%
C To learn about something interesting	128	42.7%
D Just for fun, I don’t really care how well I did in the task	90	30%
E Other, please specify.	17	5.7%

Among those who chose E (other), some example answers are “love anything to do with numbers”, “interested in contributing to scientific research”, “improve my mind, I love brain strategies”, “curiosity”, “like probabilities and gambling probabilities like poker”.

Appendix C. Study 3

1. Earned Payoff information

Table 25 and Table 26 below show the earned total bonus (mean and standard deviation), and expected total bonus for a pure matching strategy and a pure maximizing strategy (in dollars). The expected score for a pure matching strategy is $(2/3 \cdot 2/3 + 1/3 \cdot 1/3) \cdot 20 = 11.1$. Since the bonus for each single correctly predicted trial was \$0.05, the total expected bonus is $11.1 \cdot \$0.05 = \0.556 . For a pure maximizing strategy, the expected score is $2/3 \cdot 20 = 13.3$, thus the expected bonus pay is $13.3 \cdot \$0.05 = \0.667 .

Table 25. Payoff Information (Earned and Expected) for Different Types of Context

Context	Earned Bonus (Mean, Std. deviation)	Expected Bonus (Matching)	Expected Bonus (Maximizing)
Abstract	\$0.597, (.124)		
Concrete	\$0.596, (.127)	\$0.556	\$0.667
Real-world	\$0.611, (.113)		

Table 26. Payoff Information (Earned and Expected) for Different Schema Types

Schema Type	Earned Bonus (Mean, Std. deviation)	Expected Bonus (Matching)	Expected Bonus (Maximizing)
Complementary	\$0.594, (.118)	\$0.556	\$0.667
Independent	\$0.609, (.125)		

2. ANOVA Table

The following Table 27 is the ANOVA table output for the Study 3 data using the GLIMMIX procedure. The dependent variables are the binary predictions for the 20 single trials.

Table 27. ANOVA Table for Predictions

Source	F	df1	df2	P-value
Corrected Model	1.614	81	5918	<.0001
Level	.475	2	5918	.622

Schema	20.418	1	5918	<.0001
Trias	2.7	19	5918	<.0001
Level*Trials	1.173	38	5918	.216
Level*Schema	1.396	2	5918	.248
Schema*Trials	.793	19	5918	.718